A Multimodal Smartphone-Based Screening Approach for Detecting Psychophysiological Discordance in Adolescent Academic Stress

Research Proposal

Submitted to:

Student Academic Research Competition (SARC)

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Abstract

Adolescent mental health crises are frequently identified only after visible academic or behavioral decline. This study proposes a multimodal machine learning system that integrates smartphone-derived heart rate variability (HRV), sleep duration, weekly study hours, and validated psychological scales to detect burnout risk and hidden psychological distress among secondary school students aged 14-19. HRV is estimated via HRV4Training, a validated smartphone photoplethysmography (PPG) application. A novel classification category, Hidden Distress Risk, is introduced to identify students exhibiting physiological stress elevation despite low self-reported symptoms, a population invisible to questionnaire-only screening. Drawing on a primary sample of 50 students supplemented by the WESAD physiological stress dataset, multimodal models including XGBoost and Random Forest are hypothesized to outperform self-report-only screening, particularly in detecting psychophysiological discordance.

Introduction

Adolescent mental health has deteriorated markedly over the past decade. Between 2016 and 2023, diagnosed anxiety among adolescents aged 12-17 in the United States increased by 61%, with over 20% of adolescents carrying a current mental health diagnosis as of 2023 (HRSA, 2023). Globally, the World Health Organization estimates that one in seven adolescents aged 10-19 experiences a mental health condition, yet the majority go unrecognized until symptoms become severe (WHO, 2022). Despite this urgency, most school-based screening systems remain reactive, relying on teacher referrals, falling grades, or visible behavioral breakdown. This study proposes supplementing self-report data with physiological and behavioral signals. Sleep disruption is a documented precursor of academic burnout and emotional dysregulation. Weekly study hours provide a direct, low-burden measure of cognitive demand. HRV, estimated non-invasively via smartphone PPG, reflects autonomic stress regulation independently of subjective reporting (Thayer & Lane, 2000). Integrating these multimodal signals with psychological scales may enable earlier identification of distress.

Research Question

Can a multimodal machine learning model integrating smartphone-derived HRV, sleep duration, and weekly study hours accurately classify secondary school students by burnout and hidden distress risk, including those exhibiting psychophysiological discordance?

Literature Review

HRV is a validated physiological biomarker of autonomic regulation, with reduced variability consistently linked to chronic stress and impaired emotional control (Shaffer & Ginsberg, 2017). The neurovisceral integration model explains HRV as a reflection of prefrontal cortical regulation of emotional responses under sustained stress, providing a mechanistic rationale for its use as a screening signal in high-pressure academic contexts (Thayer & Lane, 2000). Adolescent academic stress is associated with burnout, reduced motivation, and emotional exhaustion (Pascoe et al., 2020), while insufficient sleep exacerbates cognitive and emotional dysregulation (Owens, 2014). Because HRV and sleep quality are physiologically interrelated, their combination is expected to strengthen classification performance.

Can et al. (2019) provide the most comprehensive survey of smartphone and wearable-based stress detection systems, demonstrating that multimodal sensor fusion consistently outperforms single-variable approaches in real-world settings. However, the systems surveyed predominantly target adult workplace populations; no validated model in their review addresses secondary school students in naturalistic academic environments. Existing school mental health screening programmes similarly rely exclusively on self-report instruments.

This absence reflects a structural gap rather than an evidence gap: the technology exists, but has not been applied to this population. This study introduces Hidden Distress Risk as a distinct classification category addressing this gap precisely, representing a contribution not yet found in the student wellbeing screening literature.

Methodology

Fifty secondary school students aged 14-19 will be recruited from a single participating institution across one academic semester. To supplement this primary sample and support more robust model training, the WESAD multimodal physiological stress dataset (Schmidt et al., 2018) will be used for feature pre-validation and initial model benchmarking, with fine-tuning performed on the primary student data. HRV will be collected using HRV4Training, a validated smartphone PPG application shown to achieve strong RMSSD agreement against ECG reference standards under resting conditions (Plews et al., 2017). To minimize device-driven signal variability, participants will be restricted to compatible iPhone models with standardized camera hardware. Each participant will complete a 2-minute resting morning PPG reading. Sleep duration and variability will be passively recorded via Apple Health. Academic workload will be measured as average weekly study hours via daily self-report. Validated psychological scales, the Perceived Stress Scale (Cohen et al., 1983) and GAD-7 (Spitzer et al., 2006), will be administered at three structured timepoints: pre-examination, mid-term, and post-examination, capturing stress variation across the academic semester. HRV features extracted will include RMSSD, SDNN, and pNN50; LF/HF ratio is excluded due to low reliability under short-term resting PPG conditions (Shaffer & Ginsberg, 2017). Hidden Distress Risk will be operationalized as a within-person HRV z-score at or below −1.0 standard deviations from individual baseline, combined with PSS below 14 and GAD-7 below 5, representing physiological stress elevation alongside minimal self-reported symptoms. Burnout Risk classification will reference MBI-SS thresholds (Schaufeli et al., 2002). XGBoost, Random Forest, and Logistic Regression models will be trained using stratified 5-fold cross-validation and evaluated via precision, F1-score, and AUC-ROC. SHAP analysis will identify dominant predictors and provide transparency in classification decisions (Lundberg & Lee, 2017).

Limitations and Ethics

PPG signal variability, individual HRV baseline differences, and student adherence inconsistency are acknowledged limitations. The 50-student sample limits generalizability but is appropriate for an exploratory pilot. Ethically, parental consent, student assent, data anonymization, and voluntary withdrawal will be implemented; the system is intended for screening support, not clinical diagnosis.

Conclusion

This study proposes a scalable multimodal AI framework for early detection of academic burnout and hidden psychological distress in secondary school students. By integrating physiological, behavioral, and self-report signals, the system aims to identify both visible burnout and psychophysiological discordance. If validated, this approach could enable schools to shift from reactive to preventive mental health support, identifying struggling students before academic or behavioral deterioration occurs. The system's reliance on consumer smartphones and a streamlined data protocol supports scalable deployment across diverse educational settings without specialized infrastructure.

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