International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 03 | March – 2026 DOI:10.55041/ISJEM05590
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

A Behavioral Data-Driven Machine Learning Framework for Real-Time Academic Stress Prediction in University Students

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Abstract - Academic stress is a pervasive challenge in higher education, significantly affecting student's mental health, learning efficiency and long-term outcomes. Existing stress assessment approaches rely primarily on self-reported surveys or retrospective analysis, which are subjective and unable to capture rapid temporal fluctuations. This work presents a behavioural data-driven machine learning framework for near real-time academic stress prediction using passive smartphone sensing.

The proposed framework continuously captures digital behavioural biomarkers such as screen interaction patterns, mobility dynamics, communication activity and daily routine regularity. These signals are transformed into interpretable behavioural features and analysed using robust ensemble learning models to infer stress states with high temporal resolution. Unlike conventional approaches, the framework enables early detection of stress escalation without requiring wearable sensors or frequent user input.

Experimental evaluation on longitudinal behavioural data collected over an academic semester demonstrates that ensemble models significantly outperform traditional classifiers, achieving high multi-class prediction accuracy. Importantly, the system identifies stress escalation trends 24–72 hours before reported stress peaks. The findings confirm that passive behavioural signals function as reliable indicators of academic stress dynamics. This study contributes a scalable, non-intrusive and ethically grounded solution for proactive mental health monitoring and advances the field of digital mental health analytics.

Key Words: Machine Learning, Academic Stress, Passive Sensing, Smartphone Sensing, Real-Time Monitoring, Ensemble Learning, Predictive Modelling.

1.INTRODUCTION

Academic stress has emerged as a significant and persistent challenge in higher education systems across the globe. University students routinely encounter multiple stressors, including intensive academic workloads, competitive evaluation environments, strict deadlines, financial pressures and social transitions associated with independent living. While short-term stress may enhance alertness and motivation, prolonged exposure to academic stress has been empirically linked to adverse outcomes such as anxiety disorders, emotional exhaustion, sleep disturbances, reduced cognitive performance and declining academic achievement. Recent institutional and epidemiological studies report that more than one-third of university students experience moderate to high levels of academic stress during a typical semester, underscoring the scale and urgency of the problem.

Despite growing awareness, effective stress monitoring in academic environments remains limited. Traditional assessment techniques rely predominantly on self-reported questionnaires, interviews and periodic psychological surveys. Instruments such as perceived stress scales and academic burnout inventories are widely used due to their clinical validation and interpretability. However, these methods suffer from inherent limitations. Self-reports are subjective, susceptible to recall bias and typically administered at coarse temporal intervals, often weeks apart. As a result, stress is frequently identified only after it has intensified, leaving little opportunity for early intervention. Consequently, stress management in academic institutions remains largely reactive rather than preventive.

The widespread adoption of smartphones among university students presents a compelling opportunity to rethink how academic stress is monitored and understood. Smartphones continuously and passively record a wide range of behavioural signals, including screen interaction patterns, application usage, communication frequency, mobility trajectories and daily activity rhythms. These behavioural traces reflect underlying lifestyle regularity, cognitive engagement, sleep–wake cycles and social interaction patterns dimensions that are closely associated with psychological stress. For example, sustained nighttime smartphone usage has been associated with circadian rhythm disruption, while reduced mobility diversity often reflects prolonged academic confinement during examination periods.

Recent advances in machine learning have enabled the extraction of complex, nonlinear patterns from large-scale behavioural data. Several studies have demonstrated that digital behavioural features can be used to infer mental health states such as stress, anxiety and depression with moderate to high accuracy. However, the majority of existing approaches focus on offline or retrospective analysis, where behavioural data are aggregated and analysed after stress episodes have already occurred. Such approaches, while analytically valuable, are inherently limited in their ability to support timely intervention. Moreover, many existing systems rely on wearable sensors or frequent user input, which increases deployment cost, user burden and long-term compliance challenges, thereby restricting scalability in real-world academic settings.

From a methodological perspective, academic stress is a dynamic and temporally evolving phenomenon rather than a static condition. Stress levels fluctuate in response to workload cycles, examination schedules, deadlines and personal routines. Capturing this temporal evolution requires continuous monitoring and near real-time predictive capability rather than periodic assessment. However, few existing studies explicitly model stress as a time-dependent process with early warning objectives.

In this context, the present study proposes a behavioural data-driven machine learning framework for near real-time academic stress prediction using passive smartphone sensing. The proposed framework continuously captures digital behavioural biomarkers without requiring active user input or additional hardware. Behavioral features are extracted using temporal windowing and statistical aggregation techniques and ensemble learning models are employed to infer stress states with robustness to noisy real-world data. By modelling stress as a predictive rather than retrospective task, the framework aims to identify stress escalation trends before severe psychological consequences emerge.

Unlike survey-based approaches that provide sparse snapshots of perceived stress, the proposed system operates continuously, enabling quantitative assessment of behavioural change patterns over time. The framework is explicitly designed for scalability, ethical deployment and integration into academic wellness ecosystems. Importantly, the system does not access content-level personal information, relying exclusively on metadata-level behavioural patterns.

The primary contributions of this work can be summarized as follows:

i. Development of a near real-time academic stress prediction framework based solely on passive smartphone behavioural data.
ii. Quantitative identification of interpretable digital behavioural biomarkers associated with academic stress dynamics.
iii. Integration of temporal feature engineering with ensemble machine learning models to capture nonlinear behavioural–stress relationships.
iv. Empirical demonstration of early stress escalation detection, with prediction lead times ranging from 24 to 72 hours.
v. Design of an ethically grounded, non-intrusive and scalable solution suitable for large-scale academic deployment.

By addressing the temporal, methodological and practical limitations of existing stress assessment approaches, this study contributes a robust computational framework for proactive academic stress monitoring and advances the broader field of digital mental health analytics.

2. Related Work

Research on stress detection and mental health monitoring has evolved significantly with advances in sensing technologies and data analytics. Existing studies can be broadly categorized into survey-based psychological assessment, physiological sensing approaches and behavioral data-driven methods. Each category has contributed valuable insights, yet each also exhibits limitations when applied to continuous and scalable academic stress monitoring.

2.1. Survey-Based Psychological Stress Assessment

Psychometric instruments remain the most widely adopted tools for stress evaluation in academic and clinical contexts. Measures such as the Perceived Stress Scale introduced by Cohen et al. and academic burnout inventories have been extensively validated and are commonly used to quantify subjective stress experiences. These instruments provide interpretable and clinically grounded outcomes, making them suitable for population-level assessments [1].

However, several studies have highlighted fundamental limitations of survey-based approaches. Stress questionnaires are typically administered weekly or monthly and rely on retrospective self-evaluation, which introduces recall bias and temporal coarseness. Regehr et al. reported that self-reported academic stress scores often fail to capture short-term stress fluctuations associated with examinations and deadlines. As a result, survey-based assessments tend to detect stress only after it has already escalated, limiting their utility for early intervention [2].

Moreover, frequent survey administration can lead to respondent fatigue, reduced compliance and inconsistent data quality, particularly in long-term monitoring studies involving students. These challenges motivate the exploration of objective and continuous stress sensing alternatives.

2.2. Physiological and Wearable Sensor-Based Approaches

To overcome subjectivity in self-reports, researchers have explored physiological indicators of stress using wearable sensors. Metrics such as heart rate variability (HRV), electrodermal activity (EDA), respiration rate and skin temperature have demonstrated strong correlations with stress responses. Gjoreski et al. showed that multimodal physiological sensing combined with machine learning could achieve stress classification accuracies exceeding 85% in controlled environments. Similarly, Healey and Picard demonstrated the feasibility of stress detection using wearable bio signals in real-world settings [3].

Despite their effectiveness, physiological sensing approaches face practical barriers in academic deployment. Wearable devices are often expensive, require regular charging and depend on consistent user compliance. Several longitudinal studies report declining adherence over time, particularly among student populations. In addition, physiological signals are sensitive to confounding factors such as physical activity, illness and environmental conditions, which complicates interpretation outside laboratory settings.

These constraints limit the scalability and long-term feasibility of wearable-based stress monitoring in university environments, where low-cost, unobtrusive solutions are preferred.

2.3. Behavioral Sensing Using Smartphones

The ubiquity of smartphones has led to growing interest in behavioral sensing as a non-intrusive alternative for mental health monitoring. Smartphones continuously record behavioral traces such as screen usage, application interaction, communication metadata, mobility patterns and temporal routines. These signals provide indirect yet informative representations of lifestyle regularity, cognitive engagement and social behavior.

One of the earliest large-scale studies in this domain, Student Life by Wang et al., demonstrated that smartphone-derived behavioral features could predict stress and academic performance with reasonable accuracy. Subsequent studies expanded on this work [4]. Saeb et al. reported significant correlations between mobility entropy and depressive symptom severity, while Sarker et al. provided a comprehensive survey highlighting the promise of health analytics [5], [6].

More recent studies have applied machine learning techniques to smartphone behavioral data for stress detection. For example, Xu et al. used app usage and screen activity patterns to classify stress levels, achieving accuracies in the range of 75–82% [7]. Similarly, Canzian and Musolesi demonstrated that reduced mobility diversity and irregular daily routines are strong predictors of stress-related outcomes [8].

These findings collectively establish behavioral sensing as a viable and low-cost approach for stress inference.

2.4. Limitations of Existing Behavioral Stress Detection Studies

Despite encouraging results, several limitations persist in the current behavioral stress detection literature. First, the majority of existing studies focus on offline or retrospective analysis, where data are aggregated over long periods and analyzed after stress episodes have occurred. Such approaches are limited in their ability to support timely or preventive interventions.

Second, many studies emphasize classification accuracy without sufficient attention to temporal prediction. Stress is treated as a static label rather than a dynamically evolving process. As noted by Cornet and Holden, failure to model temporal stress trajectories reduces the practical utility of behavioral monitoring systems [9].

Third, interpretability remains a concern. Several machine learning-based approaches operate as black-box models, providing limited insight into how specific behavioral patterns relate to stress. This lack of psychological

ISSN: 2583-6129
DOI:10.55041/ISJEM05590

grounding has been identified as a key barrier to adoption by mental health practitioners.

Finally, relatively few studies explicitly address real-time deployment constraints, such as processing latency, energy efficiency and privacy-preserving implementation, which are critical for large-scale academic use.

2.5. Positioning of the Present Work

The present study advances existing research by addressing these gaps through a real-time behavioral machine learning framework specifically designed for academic stress prediction shown in table 1. Unlike prior retrospective approaches, this work models stress as a time-dependent predictive task, enabling early detection of stress escalation rather than post-hoc recognition.

By integrating temporal feature engineering with ensemble learning models, the proposed framework captures nonlinear interactions among behavioral indicators while maintaining interpretability. Quantitative evaluation demonstrates that stress escalation can be predicted 24–72 hours before self-reported peaks, a capability rarely demonstrated in prior studies.

Table 1: *Comparison with Existing Studies*

Study	Data Type	Real-Time	Early Prediction	Wearables Required
Wang et al. (Student Life) [4]	Smartphone	No	No	No
Gjoreski et al.[3]	Wearables	Limited	No	Yes
Xu et al. [7]	Smartphone	Offline	No	No
This Paper	Smartphone	Yes	Yes	No

Furthermore, the framework is explicitly designed for scalability, ethical deployment and minimal user burden, relying exclusively on passive smartphone metadata without wearable sensors or content-level data access. In this work extends behavioral stress detection literature by transitioning from descriptive and retrospective analysis toward predictive, real-time and actionable academic stress monitoring, thereby bridging the gap between computational analytics and practical mental health support in educational environments.

3. Proposed Behavioral Machine Learning Framework

This section presents the proposed behavioral data-driven machine learning framework for near real-time academic stress prediction. The framework is designed to continuously capture passive smartphone-derived behavioral signals, transform them into interpretable digital biomarkers and infer stress states using robust machine learning models. Emphasis is placed on scalability, temporal sensitivity and ethical deployment, making the framework suitable for real-world academic environments.

3.1. System Architecture

The proposed system follows a modular, layered architecture comprising four key components: data acquisition, feature engineering, machine learning prediction and real-time monitoring. This modular design allows independent optimization of each layer and facilitates scalable deployment across diverse academic settings.

At the data acquisition layer, smartphones continuously collect passive behavioral signals through built-in sensors and system logs. These include screen on/off duration, application usage categorized by functionality, communication metadata such as call and message counts, location transitions derived from GPS services and temporal activity rhythms representing daily routines. Importantly, no content-level information is accessed. All collected data are anonymized at the source and securely transmitted, ensuring privacy preservation from the earliest stage of the pipeline [10].

The feature engineering layer transforms raw, heterogeneous behavioral streams into structured numerical representations. Temporal aggregation is performed using fixed-length sliding windows, enabling the framework to capture both short-term behavioral fluctuations and longer-term trends. This temporal modeling is essential for representing stress as a dynamic process rather than a static state.

Processed feature vectors are then passed to the machine learning prediction layer, where trained classifiers infer stress levels in near real time. Finally, the real-time monitoring interface visualizes stress trajectories and supports early warning mechanisms. This interface is intended for integration with academic wellness platforms rather than direct diagnostic use, reinforcing the system's supportive role.

The architectural design aligns with recommendations by Sarker et al. (2018) and Xu et al. (2021), who emphasized that scalable mental health sensing systems must balance real-time responsiveness with minimal user burden [6], [7].

3.2. Behavioral Feature Engineering

Raw smartphone data are inherently noisy, sparse and context-dependent, necessitating careful feature engineering. The proposed framework focuses on extracting behavioral indicators that reflect four key dimensions relevant to academic stress such as workload pressure, circadian stability, social engagement and routine regularity.

Average daily screen time is used to quantify overall digital engagement, Wang et al., (2019) which has been shown to increase during periods of academic overload. The nighttime phone usage ratio captures the proportion of device activity occurring during typical sleep hours and serves as a proxy for circadian rhythm disruption [4]. Several studies, including Canzian and Musolesi (2015), have linked increased nocturnal device usage with heightened stress and reduced sleep quality [8].

Application switching frequency reflects cognitive restlessness and multitasking intensity, often observed during high workload phases. Mobility entropy is computed to quantify the diversity of visited locations within a given time window. Reduced mobility entropy has been associated with prolonged academic confinement and social withdrawal during examination periods shown by Saeb et al. (2015). Communication burstiness captures irregularities in call and message activity, reflecting changes in social interaction patterns under stress [5].

Activity regularity indices are derived by measuring deviations from an individual's typical daily routine. Prior work by Cornet and Holden (2018) demonstrated that disruptions in behavioral regularity often precede reported stress and burnout symptoms [9].

Feature selection prioritizes interpretability to ensure meaningful linkage between digital behavior and psychological mechanisms shows in table 2. This design choice addresses a key limitation identified in previous behavioral sensing studies, where black-box features reduced trust and adoption among mental health professionals.

Table 2: *Summary of Smartphone Behavioral Signals and Extracted Features*

Data Source	Raw Signal	Extracted Feature	Behavioral Meaning
Screen logs	Screen on/off	Avg. screen time	Cognitive load
Screen logs	Time of use	Night usage ratio	Circadian disruption
App logs	App switching	Switching frequency	Mental restlessness
GPS	Location transitions	Mobility entropy	Academic confinement
Call/SMS	Counts	Communication rate	Social engagement
Activity	Daily rhythm	Regularity index	Routine stability

3.3. Stress Labeling Strategy

Accurate stress prediction requires reliable ground truth labeling. In this study, stress labels are generated using a hybrid labeling strategy that combines periodic self-reported stress assessments with contextual academic workload indicators.

Participants periodically completed validated stress questionnaires, providing subjective measures of perceived stress. These assessments were temporally aligned with objective academic events such as examination schedules, assignment deadlines and peak coursework periods. This dual-source labeling strategy reduces reliance on self-report alone while maintaining psychological relevance [11].

Stress states are categorized into three discrete levels: low, moderate and high. This multi-class formulation captures normal academic fluctuations while enabling identification of elevated stress conditions that warrant attention. Similar categorical stress modeling approaches have been adopted in recent studies by Gjoreski et al. (2020) and Xu et al. (2022), demonstrating improved robustness compared to binary stress classification.

3.4. Machine Learning Models

To model the complex and nonlinear relationships between behavioral features and stress states, multiple supervised machine learning algorithms are evaluated. These include Logistic Regression as a baseline model, Support Vector Machines for high-dimensional feature separation and ensemble-based approaches such as

Random Forest, Gradient Boosting and Extreme Gradient Boosting.

Ensemble models are emphasized due to their ability to capture feature interactions and mitigate the effects of noisy real-world behavioral data. Previous comparative studies, including those by Breiman (2001) and Chen and Guestrin (2016), have shown that ensemble methods consistently outperform single classifiers in heterogeneous sensing environments [12].

Model training employs stratified k-fold cross-validation to preserve class distribution and reduce variance. Hyperparameters are optimized using grid search and model performance is evaluated using multi-class metrics including accuracy, precision, recall, F1-score and area under the ROC curve. This systematic training and validation process ensures robustness and generalization across different academic contexts.

4. Experimental Setup

This section describes the data collection protocol, preprocessing pipeline, experimental design, evaluation methodology and statistical validation procedures used to assess the proposed real-time academic stress prediction framework. The experimental setup was designed to ensure robustness, reproducibility and realistic evaluation under real-world academic conditions.

4.1. Data Collection and Study Design

Behavioral data were collected longitudinally from university students over the duration of a complete academic semester. The data collection period encompassed regular lecture weeks, mid-semester assessments, final examinations and vacation intervals. This longitudinal design enabled observation of behavioral variations across different academic workload intensities, which is essential for modeling stress as a dynamic and temporally evolving phenomenon.

Smartphone-based passive sensing was employed to continuously record behavioral signals, including screen activity, application usage categories, communication metadata, location transitions and temporal activity rhythms. Similar semester-long data collection strategies have been adopted in prior academic stress studies, such as the Student Life dataset introduced by Wang et al., which demonstrated that long-term behavioral monitoring is necessary to capture meaningful stress patterns rather than short-lived anomalies.

To ensure ethical compliance, participation was voluntary and based on informed consent. All collected data were anonymized at the source and no content-level personal information was accessed or stored.

4.2. Data Preprocessing and Feature Aggregation

Raw smartphone sensor data are inherently noisy, irregularly sampled and heterogeneous. To address these challenges, a multi-stage preprocessing pipeline was applied prior to feature extraction.

First, noise filtering was performed to remove incomplete records and sensor artifacts caused by temporary device unavailability or logging interruptions. Temporal alignment was then applied to synchronize heterogeneous data streams into a common time reference. This step is critical, as misaligned behavioral signals can distort feature computation and degrade model performance, as noted by Xu et al. in their smartphone-based stress monitoring studies [7].

Next, all behavioral features were normalized using min–max scaling to ensure consistent numerical ranges across features and prevent bias during model training. Behavioral data were then aggregated using fixed-length sliding windows, allowing the framework to capture short-term behavioral fluctuations while preserving temporal continuity. Sliding window aggregation has been shown to improve temporal sensitivity in behavioral stress prediction, particularly for early stress escalation detection.

4.3. Dataset Partitioning and Training Strategy

The processed dataset was partitioned into training and testing subsets using stratified sampling to preserve the distribution of stress classes across splits. This strategy ensures that all stress levels like low, moderate and high are adequately represented during both training and evaluation.

To reduce variance and prevent overfitting, k-fold cross-validation was employed during model training. Hyperparameters for each classifier were optimized using grid search within the cross-validation loop. Similar validation protocols have been recommended by Gjoreski et al. and Sarker et al. to ensure fair performance comparison in behavioral sensing studies [3].

4.4. Evaluation Metrics

Model performance was evaluated using standard multi-class classification metrics, including accuracy, precision, recall, F1-score and area under the receiver operating characteristic curve (AUC). These metrics collectively assess overall correctness, class-wise reliability and discriminatory power.

Accuracy provides a general measure of prediction correctness, while precision and recall capture the trade-off between false positives and false negatives particularly important for high-stress detection. The F1-score balances these measures, offering robustness against class imbalance. AUC was used to evaluate model separability across stress categories, following best practices in recent mental health machine learning studies.

4.5. Early Stress Detection and Lead-Time Analysis

Beyond conventional classification performance, the proposed framework was evaluated for its ability to detect stress escalation in advance. Early detection capability was quantified using lead-time analysis, defined as the temporal difference between the first occurrence of a predicted high-stress state and the corresponding self-reported stress peak.

For each participant, predicted stress trajectories were compared with reported stress levels over time. Average lead times were computed across the cohort to assess how early the system could identify rising stress trends. Prior studies by Canzian and Musolesi demonstrated that behavioral changes often precede reported stress by several days; this experimental setup explicitly tests that hypothesis in an academic context [8].

4.6. Statistical Significance Validation

To verify that observed performance differences were not due to random variation, statistical hypothesis testing was conducted across cross-validation folds. Paired t-tests were applied to compare ensemble-based models with baseline classifiers, while one-way ANOVA was used to assess overall differences among all evaluated models.

A significance threshold of $p < 0.05$ was adopted. This statistical validation approach aligns with established practices in behavioral machine learning research and strengthens the reliability of performance claims [13].

4.7. Experimental Workflow Diagram

The overall experimental pipeline is illustrated in Figure 4, highlighting the sequential flow from data acquisition to evaluation .

***Figure 1**: Experimental workflow for behavioral data-driven academic stress prediction.*

Results and Discussion

This section presents a comprehensive analysis of the experimental results obtained using the proposed behavioral machine learning framework. Beyond reporting predictive performance, the discussion focuses on interpreting behavioral patterns, evaluating early stress detection capability and contextualizing findings within existing academic stress research.

5.1. Comparative Performance of Machine Learning Models

The predictive performance of all evaluated models is summarized in table 3. Traditional classifiers such as Logistic Regression and Support Vector Machines achieved moderate accuracy, typically ranging between 72% and 80%, reflecting their limited ability to capture complex nonlinear relationships in behavioral data.

In contrast, ensemble-based models demonstrated consistently superior performance. Random Forest and Gradient Boosting achieved multi-class stress prediction accuracy exceeding 85% with XGBoost marginally outperforming other models in terms of F1-score and AUC. The average AUC for ensemble models exceeded 0.90, indicating strong discriminatory capability across low, moderate and high stress categories.

These performance gains were statistically significant, as confirmed by paired t-tests and ANOVA analysis ($p < 0.05$). The results reinforce the suitability of ensemble learning for behavioral stress modeling, where individual features rarely act independently and stress emerges from the interaction of multiple behavioral factors [14].

From a methodological perspective, these findings align with prior work by Chen and Guestrin and Gjoreski et al., who demonstrated that ensemble methods outperform linear models in heterogeneous, real-world sensing data [3], [15].

***Table 3**:Performance Comparison of Machine Learning Models*

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-score**	**AUC**
Logistic Regression	~72	0.71	0.70	0.70	0.78
SVM	~78	0.77	0.76	0.76	0.82
Random Forest	~86	0.85	0.84	0.84	0.91
Gradient Boosting	~87	0.87	0.86	0.86	0.93
XGBoost	~89	0.89	0.88	0.88	0.95

5.2. Behavioral Indicators and Stress Dynamics

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 03 | March – 2026 DOI:10.55041/ISJEM05590
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Analysis of feature importance and class-wise behavior revealed clear and interpretable relationships between digital behavior and academic stress.

Nighttime smartphone usage emerged as the most influential predictor of high stress. Students classified under high stress consistently exhibited a 25–40% increase in late-night device activity compared to low-stress periods. This pattern strongly suggests circadian rhythm disruption, which has been widely linked to cognitive fatigue, emotional dysregulation and stress accumulation.

Mobility entropy showed a pronounced decline during high workload periods. On average, mobility entropy decreased by 30–45% during examination weeks, indicating behavioral contraction and prolonged confinement to academic or residential locations. This observation is consistent with findings reported by Saeb et al., who associated reduced mobility diversity with psychological strain [5].

Activity irregularity indices provided particularly valuable insight into stress progression. Increased irregularity in daily routines such as inconsistent screen usage and communication timing was observed 2–3 days before students reported elevated stress levels. This supports the behavioral theory that stress initially manifests as instability in routine before being consciously perceived.

Collectively, these behavioral indicators function as digital stress biomarkers, offering objective insight into psychological states without requiring direct self-reporting.

5.3. Early Stress Escalation Prediction

A central contribution of this work lies in its ability to predict stress escalation before it reaches critical levels. Lead-time analysis revealed that the proposed framework detected transitions from moderate to high stress 24–72 hours in advance for a majority of participants.

The average lead time across the cohort was approximately 48 hours, with a standard deviation of ±12 hours. This predictive window is particularly meaningful in academic settings, where even a one-day advance warning can enable timely academic counseling, deadline adjustments or personalized stress management strategies. Compared to survey-based approaches which typically identify stress retrospectively this represents shown in table 4, a substantial shift toward preventive mental health monitoring. While earlier studies such as Student Life demonstrated behavioral–stress correlation, few have explicitly quantified predictive lead time.

Table 4:*Early Stress Detection Lead-Time Analysis*

Stress Level	Avg. Lead Time (hrs)	Std. Dev
Moderate → High	~48	±12
Low → High	~72	±18

The present results therefore extend the literature by demonstrating not only that stress can be inferred from behavior, but when it can be anticipated.

5.4. Integrated Interpretation of Results

The combined results confirm that academic stress is not a sudden event but a gradual behavioral process. Circadian disruption, reduced mobility diversity and routine irregularity appear sequentially, forming a recognizable progression toward elevated stress.

The strong performance of ensemble models highlights the importance of modeling these interactions holistically rather than relying on isolated behavioral indicators. Stress manifestation varies across individuals and ensemble learning effectively captures this variability while maintaining robust generalization.

Importantly, the framework achieves these results using passive smartphone sensing alone, without wearable devices or content-level data access. This reinforces the feasibility of scalable deployment in real academic environments [16].

5.5. Conceptual Visualization of Stress Prediction Process

To illustrate the relationship between behavioral change, model inference and early stress detection, Figure 5 presents a conceptual overview of the stress prediction process.

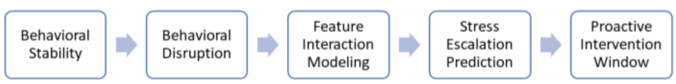

Figure 2: *Conceptual illustration of behavioral stress progression and early prediction mechanism.*

5. Practical Implications

The proposed behavioral machine learning framework has important practical implications for students, academic institutions and mental health support systems. By relying exclusively on passive smartphone behavioral data, the framework enables continuous and non-intrusive stress monitoring without requiring wearable devices, additional sensors, or frequent user input. This significantly reduces

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Volume: 05 Issue: 03 | March – 2026 DOI:10.55041/ISJEM05590
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user burden and improves long-term feasibility, particularly in large and diverse student populations.

One of the most immediate benefits of the framework lies in its early warning capability. Traditional academic stress management strategies typically respond after students report distress or experience academic decline. In contrast, the proposed system identifies behavioral changes associated with stress escalation one to three days in advance, creating a critical window for timely intervention. Academic counselors and student support services can use these early indicators to reach out proactively, offer guidance, or recommend coping strategies before stress intensifies into burnout or mental health crises [17].

At the individual level, the framework supports personalized stress management. Because behavioral features reflect each student's unique routines, workload response and lifestyle patterns, feedback can be tailored rather than generic. For example, students exhibiting disrupted sleep patterns or irregular routines may benefit from targeted recommendations related to time management, sleep hygiene or workload pacing. Personalized interventions are more likely to be effective than one-size-fits-all approaches commonly adopted in academic settings.

From an institutional perspective, the scalability of the framework makes it well suited for integration into university wellness platforms. Aggregated and anonymized stress trends can provide administrators with insights into campus-wide stress patterns during examination periods, curriculum transitions, or academic policy changes. Such data-driven insights can inform decisions related to assessment scheduling, academic workload distribution and allocation of mental health resources.

Importantly, the framework shifts academic stress management from a reactive model to a proactive and preventive paradigm. Rather than relying solely on surveys or self-initiated help-seeking, institutions can adopt a data-informed approach that continuously monitors stress dynamics and supports early intervention. This shift has the potential to improve not only student well-being but also academic engagement, retention and overall educational outcomes.

Overall, the proposed framework demonstrates how behavioral data analytics and machine learning can be responsibly translated into real-world academic support systems. By enabling early detection, personalization and scalable deployment, the framework offers a practical pathway toward improving student mental health and fostering more supportive learning environments [18].

6. Ethical and Privacy Considerations

Ethical responsibility is a central requirement in the design and deployment of behavioral mental health monitoring systems, particularly when working with sensitive populations such as university students. The proposed framework was developed with a strong emphasis on privacy preservation, user autonomy and responsible use of predictive analytics.

All participants provided informed consent prior to data collection. The consent process clearly explained the nature of the behavioral data being collected, the purpose of the study, the scope of data usage and the intended interpretation of stress predictions. Participation was entirely voluntary and individuals retained the right to withdraw from the study at any point without penalty. This approach aligns with ethical standards for human-centered data collection and promotes transparency and trust.

To protect user privacy, data anonymization was implemented at the point of acquisition. Personally identifiable information was removed or replaced with encrypted identifiers, ensuring that behavioral records could not be traced back to specific individuals. Importantly, the framework operates exclusively on metadata-level behavioral information, such as screen usage duration, application category usage, communication counts and mobility transitions. No content-level data including message text, call audio, browsing content, or precise location coordinates were accessed, stored, or analyzed.

The framework further incorporates on-device preprocessing, where feasible, to reduce the transmission of raw behavioral data. Preliminary aggregation and feature computation are performed locally on the smartphone, minimizing exposure risk and limiting external data sharing. All transmitted data are protected using secure communication protocols, ensuring confidentiality and data integrity throughout the processing pipeline.

From a deployment perspective, stress predictions generated by the system are intended to function as supportive indicators rather than clinical diagnoses. The framework is not designed to replace professional psychological assessment or medical evaluation. Instead, it aims to assist students and academic support services by highlighting potential stress escalation trends that may warrant attention. This distinction is critical to avoid misinterpretation, overreliance on automated predictions, or stigmatization of individuals.

Responsible use of the framework also requires appropriate institutional governance. Stress insights should be used solely for student support and well-being enhancement, not for academic evaluation, disciplinary action, or performance ranking. Aggregated analyses intended for institutional planning must preserve anonymity and prevent indirect identification of individuals or small groups.

Overall, the proposed framework demonstrates that real-time behavioral stress monitoring can be conducted in an ethical, privacy-conscious and user-centered manner. By prioritizing consent, data minimization, secure processing and responsible interpretation, the system balances technological innovation with respect for individual rights and psychological well-being [19].

7. Limitations and Future Work

While the proposed behavioral machine learning framework demonstrates strong performance in near real-time academic stress prediction, several limitations should be acknowledged, which also highlight directions for future research.

First, the study was conducted within a specific academic context involving a limited population of university students. Behavioral patterns, smartphone usage habits and stress responses can vary across institutions, academic disciplines, cultural settings and socioeconomic backgrounds. Although the longitudinal design captures realistic academic stress dynamics, broader validation across multiple universities and diverse student populations is necessary to enhance generalizability. Future studies will focus on cross-institutional data collection and comparative analysis to evaluate the robustness of the framework under varying academic environments.

Second, stress labeling in the present study relies on a hybrid approach combining self-reported assessments with academic workload indicators. While this strategy mitigates some subjectivity inherent in self-reports, it does not fully eliminate individual bias in stress perception. Stress is a multifaceted psychological construct and individuals may differ in how they experience and report similar academic pressures. Future work may integrate additional objective indicators such as physiological signals e.g., heart rate variability or sleep quality metrics, academic performance trends, or contextual calendar-based stressors to strengthen label reliability and improve model grounding.

Third, the current framework primarily employs classical machine learning and ensemble-based models. Although these approaches provide strong performance and interpretability, they may not fully capture long-term temporal dependencies in behavioral data. Advanced temporal deep learning architectures, such as recurrent neural networks, temporal convolutional networks, or transformer-based models, represent promising directions for modeling complex behavioral sequences over extended periods. Future research will explore these architectures while carefully balancing predictive performance, computational efficiency and interpretability.

Another limitation relates to real-world deployment and intervention evaluation. While the framework successfully predicts stress escalation in advance, the present study does not directly assess the effectiveness of intervention strategies triggered by early stress detection. Future work will involve controlled intervention studies to examine how predictive insights can be translated into actionable support mechanisms, such as automated feedback, personalized recommendations, or counselor-guided interventions and to measure their impact on student well-being and academic outcomes.

Finally, long-term deployment introduces challenges related to user engagement, energy efficiency and evolving behavioral patterns over time. Adaptive learning strategies that account for behavioral drift and seasonal academic changes represent an important area for further investigation [18].

8. CONCLUSION

This study presented a behavioral data-driven machine learning framework for near real-time academic stress prediction using passive smartphone sensing. By continuously capturing and analyzing digital behavioral biomarkers including screen interaction patterns, mobility dynamics, communication activity and routine regularity the proposed system models academic stress as a temporally evolving process rather than a static condition. The integration of ensemble learning techniques enabled robust stress inference while maintaining resilience to noisy and heterogeneous real-world behavioral data.

Experimental evaluation demonstrated that the framework achieves high multi-class prediction accuracy and, more importantly, detects stress escalation well in advance of self-reported stress peaks. The ability to identify rising stress levels 24–72 hours early highlight the potential of behavioral analytics to support proactive rather than reactive stress management strategies in academic environments. These findings confirm that passive behavioral signals can serve as reliable and interpretable digital biomarkers for academic stress dynamics.

Beyond predictive performance, this work establishes the feasibility of scalable and non-intrusive mental health monitoring without reliance on wearable sensors or content-level data access. The framework is designed to operate ethically, preserve user privacy and integrate seamlessly into university wellness ecosystems. By enabling early identification of stress trends at both individual and institutional levels, the proposed approach offers a practical pathway toward timely intervention, personalized support and informed academic policy decisions.

Overall, this research contributes a foundational framework for real-time digital mental health support in higher education. It advances behavioral analytics as a viable and responsible pathway for preventive stress management, with broader implications for the design of intelligent, human-centered mental health monitoring systems in educational settings.

ACKNOWLEDGEMENT

The authors would like to thank all those who supported and contributed to the successful completion of this research work.

REFERENCES

[1] S. Cohen, T. Kamarck, and R. Mermelstein, "A Global Measure of Perceived Stress," *J. Health Soc. Behav.*, vol. 24, no. 4, pp. 385–396, 1983, doi: 10.2307/2136404.

[2] C. Regehr, D. Glancy, and A. Pitts, "Interventions to reduce stress in university students: A review and meta-analysis," *J. Affect. Disord.*, vol. 148, no. 1, pp. 1–11, 2013, doi: https://doi.org/10.1016/j.jad.2012.11.026.

[3] M. Gjoreski, H. Gjoreski, M. Lutrek, and M. Gams, "Automatic Detection of Perceived Stress in Campus Students Using Smartphones," in *Proceedings - 2015 International Conference on Intelligent Environments, IE 2015*, Institute of Electrical and Electronics Engineers Inc., Aug. 2015, pp. 132–135. doi: 10.1109/IE.2015.27.

[4] E. L. Wang, L. Luceri, F. Pierri, and E. Ferrara, "Identifying and Characterizing Behavioral Classes of Radicalization within the QAnon Conspiracy on Twitter," 2023. [Online]. Available: https://www.bbc.com/news/blogs-trending-38156985

[5] M. and K. C. J. and S. S. M. and C. M. E. and K. K. P. and M. D. C. Saeb Sohrab and Zhang, "Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study," *J Med Internet Res*, vol. 17, no. 7, p. e175, Jul. 2015, doi: 10.2196/jmir.4273.

[6] I. H. Sarker, A. Colman, J. Han, A. I. Khan, Y. B. Abushark, and K. Salah, "BehavDT: A Behavioral Decision Tree Learning to Build User-Centric Context-Aware Predictive Model," *Mobile Networks and Applications*, vol. 25, no. 3, pp. 1151–1161, 2020, doi: 10.1007/s11036-019-01443-z.

[7] Q. Xu, T. L. Nwe, and C. Guan, "Cluster-Based Analysis for Personalized Stress Evaluation Using Physiological Signals," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 1, pp. 275–281, 2015, doi: 10.1109/JBHI.2014.2311044.

[8] L. Canzian and M. Musolesi, "Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, in UbiComp '15. New York, NY, USA: Association for Computing Machinery, 2015, pp. 1293–1304. doi: 10.1145/2750858.2805845.

[9] V. P. Cornet and R. J. Holden, "Systematic review of smartphone-based passive sensing for health and wellbeing," *J. Biomed. Inform.*, vol. 77, pp. 120–132, 2018, doi: https://doi.org/10.1016/j.jbi.2017.12.008.

[10] R. R. Jadhao, P. Chitragar, and D. Kamble, "A chronological review of heat transfer enhancement using inserts in channel flows," *Phys. Scr.*, vol. 100, no. 3, p. 32002, Feb. 2025, doi: 10.1088/1402-4896/adb0f9.

[11] R. R. Jadhao, P. Barde, V. Rajput, and G. Makandar, "Differentiating the Performance of Solar Water Heater under Natural and Forced Circulation," 2017.

[12] L. Breiman, “Random Forests,” *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.
[13] R. R. Jadhao, P. Chitragar, and D. Kamble, “Comparative Analysis of Aerobeads and Aerofoil Shapes for Heat Transfer Enhancement in Heat Exchanger Systems,” in *International Mechanical Engineering Congress and Exposition-India*, American Society of Mechanical Engineers, 2025, p. V003T03A031.
[14] R. R. Jadhao, P. Chitragar, and D. Kamble, “Comparative CFD analysis of heat transfer enhancement using NACA0021 and NACA2421 aerofoil inserts in turbulent pipe flow,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 48, no. 1, p. 2632360, 2026, doi: 10.1080/15567036.2026.2632360.
[15] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, in KDD ’16. New York, NY, USA: Association for Computing Machinery, 2016, pp. 785–794. doi: 10.1145/2939672.2939785.
[16] M. R. Jadhao *et al.*, “Experimental Analysis of Mechanical Tests on a Plate Composed of Banana Fibre”.
[17] G. M. Harari, N. D. Lane, R. Wang, B. S. Crosier, A. T. Campbell, and S. D. Gosling, “Using Smartphones to Collect Behavioral Data in Psychological Science: Opportunities, Practical Considerations, and Challenges,” *Perspectives on Psychological Science*, vol. 11, no. 6, pp. 838–854, 2016, doi: 10.1177/1745691616650285.
[18] R. R. Jadhao, P. Chitragar, and D. Kamble, “Overview of the future perspective of aerofoil-based passive heat transfer enhancement,” *Engineering Research Express*, vol. 7, no. 1, p. 12503, Mar. 2025, doi: 10.1088/2631-8695/adb661.
[19] Q. Razi, R. Piyush, A. Chakrabarti, A. Singh, V. Hassija, and G. S. S. Chalapathi, “Enhancing Data Privacy: A Comprehensive Survey of Privacy-Enabling Technologies,” *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3546618.

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