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Stress-Aware Learning Management Systems Using Passive Digital Behaviour of College Students

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Abstract: *Stress significantly affects students' academic performance, well-being, and retention. Traditional stress assessment methods (surveys, self-reports) are limited by subjectivity and recall bias. Recent research focuses on passive digital behaviour monitoring to infer stress, offering real-time, scalable, and unobtrusive insights. This review synthesizes current approaches, technologies, and research gaps in stress-aware Learning Management Systems (LMSs) leveraging passive digital data from college students.*

Keywords: Learning Management Systems

I. INTRODUCTION

Stress among college students is a global concern, linked with anxiety, depression, poor academic performance, and dropout. Traditional measurement relies on surveys or clinical assessments, which are episodic and intrusive. Passive digital behaviour analysis-capturing data from smartphones, LMS usage logs, and wearable sensors-enables continuous monitoring without interrupting users.

A Stress-Aware LMS integrates behavioural signals into educational platforms to adapt content, pacing, and support mechanisms, enhancing learning outcomes and well-being.

II. BACKGROUND AND DEFINITIONS

2.1 Stress in Academic Context

Academic stress arises from workload, deadlines, social pressure, and performance expectations. Chronic stress impairs cognitive functions critical for learning, including memory, attention, and executive control.

2.2 Passive Digital Behaviour

Refers to automatically collected data without explicit user input:

- Device usage patterns: screen time, app switching, idle time
- Interaction logs: clickstreams, time spent on LMS modules
- Physiological signals: heart rate, sleep patterns (via wearables)
- Communication patterns: typing speed, social media activity

2.3 Stress-Aware LMS

An LMS that detects student stress levels and dynamically adapts teaching strategies:

- Personalized pacing
- Timely recommendationsl
- Alerts to counselors
- Stress-reduction interventions (e.g., breaks, mindfulness prompts)

III. PASSIVE DIGITAL BEHAVIOUR FOR STRESS DETECTION

3.1 Data Sources

1. Smartphone Sensors

- Accelerometer, gyroscope → physical activity
- Screen usage → sleep disruption or procrastination
- App usage → behavioural patterns

2. LMS Interaction Logs

- Time on task
- Failed quiz attempts
- Sequence of activities

3. Wearable Devices

- Heart rate variability
- Sleep duration and quality

4. Communication Metadata

- Texting frequency
- Response times

IV. METHODS FOR STRESS INFERENCE

4.1 Feature Extraction

- Time-based metrics (e.g., session length)
- Frequency counts (e.g., login frequency)
- Physiological metrics (e.g., HRV)

4.2 Machine Learning Models

- Supervised and unsupervised models used in research:
- Classification (SVM, Random Forest)
- Deep learning (LSTM for temporal patterns)
- Clustering for behavioural segmentation

4.3 Validation Approaches

- Ground truth via validated stress scales (e.g., Perceived Stress Scale)
- Correlation with academic outcomes
- Cross-validation techniques

V. INTEGRATION WITH LEARNING MANAGEMENT SYSTEMS

5.1 Adaptive Content Delivery

Stress levels trigger:

- Slower pacing
- Shorter modules
- Simplified summaries

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5.2 Feedback and Support

- Automated nudges for breaks
- Personalized motivation messages
- Alerts to instructors or advisors

5.3 Ethical and Privacy Considerations

- Informed consent
- Data anonymization
- Transparency on data use
- Compliance with regulations (e.g., GDPR)

VI. KEY FINDINGS IN LITERATURE

6.1 Predictive Accuracy

Studies show moderate to strong correlations between passive signals and stress indicators, with variants depending on data source and model.

6.2 Behaviour Patterns Indicative of Stress

- Irregular sleep, high screen time, high LMS task switching
- Reduced engagement with core academic modules
- Increased use of distraction apps

6.3 Benefits

- Early detection of stress trends
- Real-time adaptation of learning experience
- Potential reduction in dropout rates

6.4 Limitations

- Variability across individuals
- Confounds (e.g., social use vs academic use)
- Data sparsity (missing smartphone or wearable data)

VII. CHALLENGES AND GAPS

7.1 Data Quality

Inconsistent logging and noisy signals affect model reliability.

7.2 Personalization

Stress manifests differently per individual; models must be adaptive.

7.3 Ethical Concerns

Privacy, informed consent, sensitive data handling.

7.4 Scalability

Integrating real-time analysis into existing LMS infrastructure is non-trivial.

VIII. FUTURE DIRECTIONS

1. Multimodal Integration

Combine behavioural, physiological, and contextual data

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2. Real-World Deployments
Longitudinal studies in diverse academic settings
3. Explainable Models
Transparent Al to justify stress predictions
4. Interventional Studies
Measure impact of stress-aware LMS on performance and well-being

IX. CONCLUSION

Stress-aware LMS frameworks using passive digital behaviour show promising potential for early detection and mitigation of academic stress. While research demonstrates feasibility, significant work remains in personalization, ethical frameworks, and seamless institutional integration.

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