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Article

COGNITIVE STRESS MONITORING AND LEARNING SUPPORT SYSTEM FOR STUDENTS

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Abstract: Students' concentration, memory, reasoning and overall assessment are adversely impacted by stress. Traditional evaluation systems are mainly centered on grades and fail to take stress into account when assessing learning outcomes. The present study proposes the Cognitive Stress Monitoring and Learning Support System for Students which combines cognitive assessment and stress analysis for providing a more comprehensive evaluation of student performance. The system assesses student performance in five cognitive areas and measures the time taken to respond and includes physiological data like heart rate and heart rate variability (HRV). The system identifies weak areas, stress-prone tasks using a Random Forest classifier for stress and performance analysis, it can generate personalized study and stress-management suggestions via the FLAN-T5 Large Transformer model. The proposed system provides a systemic strategy to enhance student well-being and academic development.
Keywords: Cognitive Stress Monitoring, Cognitive Assessment, Heart Rate Variability (HRV), Personalized Learning Support, Stress Analysis.

1. INTRODUCTION

Academic stress is one of the major issues in the teaching and learning process today which has tremendous impact on the concentration, memory, reasoning and academic performance of students (Kim et al., 2018; Shaffer & Ginsberg, 2017). Stress can occur during exams and assessments when time is limited, difficult questions are posed and/or when there is a performance pressure. These factors may have a negative impact on cognitive processes and hinder students' performance of their abilities. But conventional evaluation systems do not pay much attention to the factors that influence students' performance, they only pay attention to the score and the time it takes.

The development of intelligent systems that can analyze both cognitive performance and stress level simultaneously has been made possible by advances in technology, including educational technology, AI, and physiological sensing (Islam Ovi et al., 2025; Singh et al., 2024). The knowledge of the impacts of stress on learning outcomes can support students, teachers and institutions in making better decisions if it comes to learning outcome and student well-being.

This study integrates cognitive evaluation with stress analysis, called the Cognitive Stress Monitoring and Learning Support System for Students. The system assesses students in five cognitive domains: numerical ability, logical reasoning, applied reasoning, verbal reasoning and working memory (Sternberg, 2022). In assessments it stores response times and, physiological measures like heart rate (HR) or heart rate variability (HRV), by integrating sensors.

Assessment data is easily tracked and analysed using student performance data, and timing logs and health information are securely stored in Supabase PostgreSQL database, with health information also collected and securely stored. Additionally, the system incorporates open-source language models through the API of the Hugging Face organization to offer custom recommendations, like study strategies, improvement tips, and stress management strategies. Specifically, a random forest (RF) classifier is adopted to predict stress and perform analysis, and the FLAN-T5 Large Transformer (Longpre et al., 2023; Chung et al., 2024) is used to generate adaptive and personalized learning support suggestions. The system proposed for the study process can not only be used for determining cognitive performance, but can also serve as a detailed analysis of the student's learning behaviour and its relation with the indicators of academic success and the psychological health of the student is required.

2. MATERIALS AND METHODS

2.1 Research Design

The study design applied in this study was quantitative research design which was used for assessing the relationship between cognitive performance and the stress level of the assessment activity. A web-based Cognitive Stress Monitoring and Learning Support System was designed for the collection of data from assessment responses, physiological stress markers and performance data. This study combines the cognitive assessment, stress prediction using machine learning techniques, and generation of recommendations using AI techniques in an integrated manner (Breiman, 2001; Singh et al., 2024, Woolf et al, Yerkes et al.). Cognitive Load theory requires essential needs of monitoring stress levels at instance of particular individual according to Sweller et al., Spielberger et al.)

2.2 Participants and Validation

In this study, the student who participated in the cognitive assessment process was voluntary. Convenience sampling was used to select participants, based on availability and willingness to participate. There were 120 students who were studying various courses. Data validation was done by discarding incomplete form, duplicate and invalid assessment data. Assessment sessions that were omitted from the final analysis were incomplete and/or invalid.

2.3 Assessment Instruments and Data Collection

The developed system evaluates cognitive performance across five domains:

- Numerical Ability
- Logical Reasoning
- Applied Reasoning
- Verbal Reasoning
- Working Memory

Images were also given as a part of questions (Sternberg, 2022). During each assessment session, the system collected:

- Domain-wise scores
- Total assessment score
- Question response time
- Heart Rate (HR)

- Heart Rate Variability (HRV)

Heart rate and heart rate variability data were collected continuously during the assessment using a wearable MAX30105 sensor attached to the participant's finger (Kim et al., 2018; Shaffer & Ginsberg, 2017; Maxim Integrated, 2020). All assessment records, timing logs, physiological measurements, and user information were securely stored in a Supabase PostgreSQL database for subsequent analysis.

Sample Questionnaire

The cognitive assessment consisted of diverse questions distributed across five cognitive domains: Numerical Ability, Logical Reasoning, Applied Reasoning, Verbal Reasoning, and Working Memory. Sample questions from each domain are presented below (Open Psychometrics, 2024; Aptitude-Test.com, 2025; Scribd, 2024).

1. Logical Reasoning

How is Kesav's mother-in-law's only daughter's daughter related to Kesav?

A. Daughter B. Niece C. Granddaughter D. Sister

2. Numerical Ability

It takes two machines at a toy factory 50 minutes to create ten (10) teddy bears. How many teddy bears can one machine create in 30 minutes?

A. 2 B. 3 C. 4 D. 5

3. Applied Reasoning

A team member agrees with everything during discussions but later fails to follow through on decisions. What is the MOST likely underlying issue?

A. Lack of understanding or commitment B. Strong leadership skills

C. Effective communication D. High productivity

4. Verbal Reasoning

Fate smiles ______ those who untiringly grapple with stark realities of life.

A. on B. at C. over D. upon

5. Working Memory

(First two image patterns, Pattern A and Pattern B, are displayed to the participant.)

Identify the change between Pattern A and Pattern B.

A. Shape position changed B. Shape rotation changed

C. Shape color changed D. Shape size changed

2.4 Stress Prediction and Performance Analysis

The relationship between cognitive performance and physiological stress indicators were analysed using a Random Forest Classifier (Breiman, 2001). The model used as the input features were domain-wise scores, total score, response time, heart rate, and heart rate variability. The Random Forest classifier was trained using labeled assessment records containing cognitive scores, response timing information, heart rate, and heart rate variability measurements collected during assessment sessions.

The Random Forest classifier classified students into stress categories (Islam Ovi et al., 2025; Singh et al., 2024):

- Low Stress
- Moderate Stress
- High Stress

The model also analyzed overall performance patterns and identified weak cognitive domains based on domain-wise assessment scores. Question timing information was further examined to determine stress-prone assessment activities and performance variations across cognitive domains. The overall workflow of the proposed system, including cognitive assessment, stress prediction using the Random Forest classifier, weak domain identification, and personalized recommendation generation using the Hugging Face model, is presented in Algorithm 1.

Algorithm 1 Cognitive Stress Monitoring and Learning Support Framework

Input: Student Credentials U, Assessment Questions Q
Output: Stress Prediction and Personalized Learning Recommendations

Authenticate student and initialize assessment session
Generate cognitive assessment covering:
- Numerical Ability
- Logical Reasoning
- Applied Reasoning
- Verbal Reasoning
- Working Memory

for each question $q_i \in Q$ **do**
    Record student response r_i
    Measure response time:

$$RT_i = t_{end} - t_{start}$$

    if physiological sensor available **then**
        Acquire Heart Rate (HR) and Heart Rate Variability (HRV)
    end if
end for
Calculate domain-wise cognitive scores:

$$S_d = \sum C_i$$

Compute total assessment score:

$$TS = \sum_{d \in D} S_d$$

Construct feature set:

$$X = \{S_d, TS, RT, HR, HRV\}$$

Predict stress category using Random Forest:

$$P = RF(X)$$

Determine weakest cognitive domain:

$$WD = \arg\min(S_d)$$

Create assessment summary:

$$A = \{P, WD, S_d, RT\}$$

Provide summary A as input to the FLAN-T5 Large Transformer
Generate personalized study strategies, topic improvement suggestions, stress-management guidance, and learning recommendations
Store assessment results and recommendations in Supabase
Present cognitive scores, stress category, weak domains, and recommendations
    return Final Cognitive Stress Assessment Report

2.5 Recommendation Generation

The results of the Random Forest classifier such as the predicted stress level, performance analysis, weak cognitive domains, and insights from timing were synthesized into a summary. This summary was provided as input to the FLAN-T5 Large Transformer model through the Hugging Face API (Chung et al., 2024; Longpre et al., 2023). The recommendations provided by the model based on the analysis of the assessment results, are:

- Topic-wise improvement suggestions
- Study strategies
- Focus enhancement techniques
- Time management guidance
- Stress management recommendations

This method involves predicting student performance using machine learning and offering personalized learning assistance through AI. The overall architecture of the proposed Cognitive Stress Monitoring and Learning Support System is shown in Figure 1. This system brings cognitive assessment, stress monitoring, prediction based on machine learning and AI recommendation generation together in a single system.

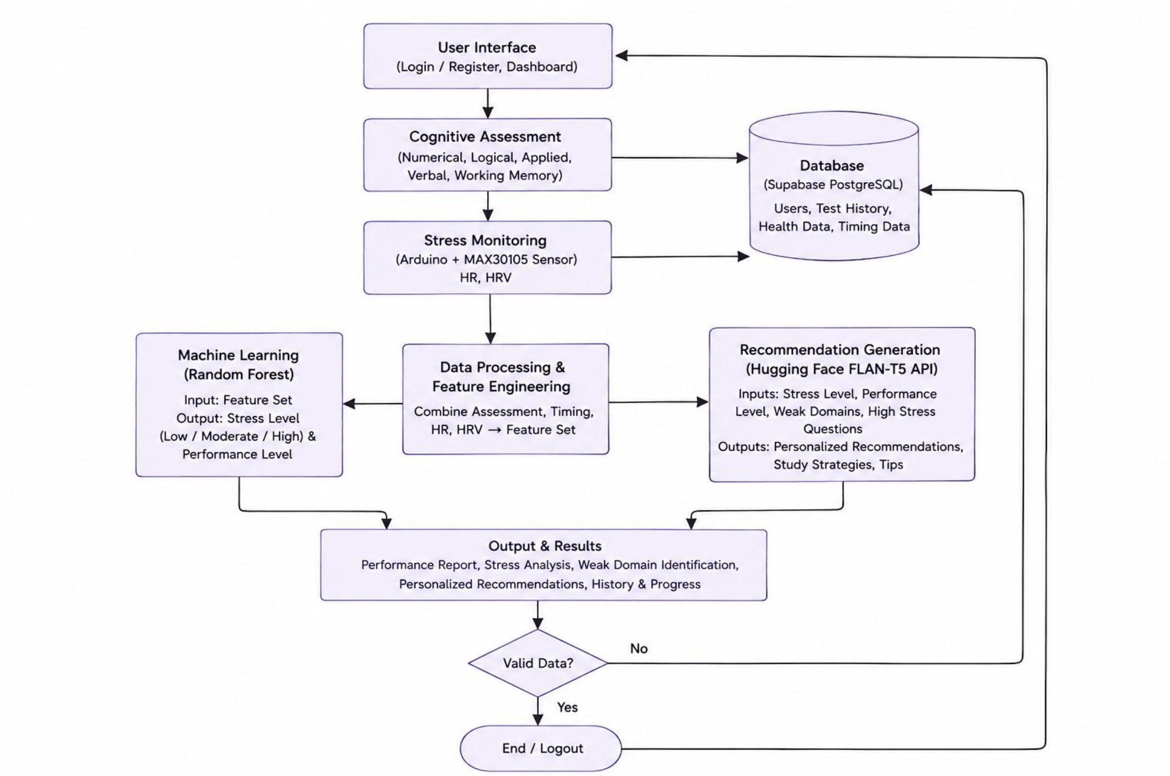

Figure 1. Architecture of the Cognitive Stress Monitoring and Learning Support System.

2.6 Ethical Considerations

The study was voluntary and informed consent was gained from all participants prior to data collection. All data gathered was secured and confidential with limited access. It was not mandatory for the participants to continue with the study. The research was carried out only for educational and academic purposes and privacy, confidentiality and data security have been maintained.

3. RESULTS AND DISCUSSION

A total number of 120 student assessment responses were gathered and analysed with the proposed Cognitive Stress Monitoring and Learning Support System. This system was able to assess cognitive abilities in five cognitive domains, measure stress through heart rate and heart rate variability, and provide individual recommendations based on the assessment results.

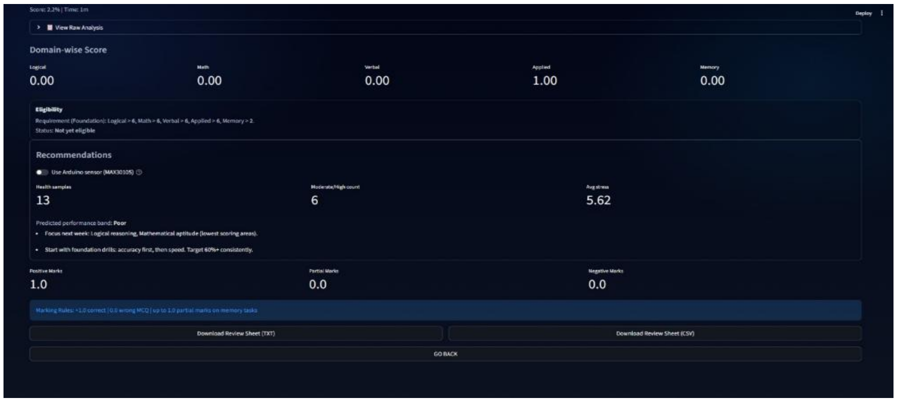

Figure 2. Cognitive Assessment and Stress Analysis Dashboard

Figure 2 demonstrates cognitive assessment result, the stress analysis result, the scores in each domain, the classification of performance, and the identification of weak domains from the cognitive assessment.

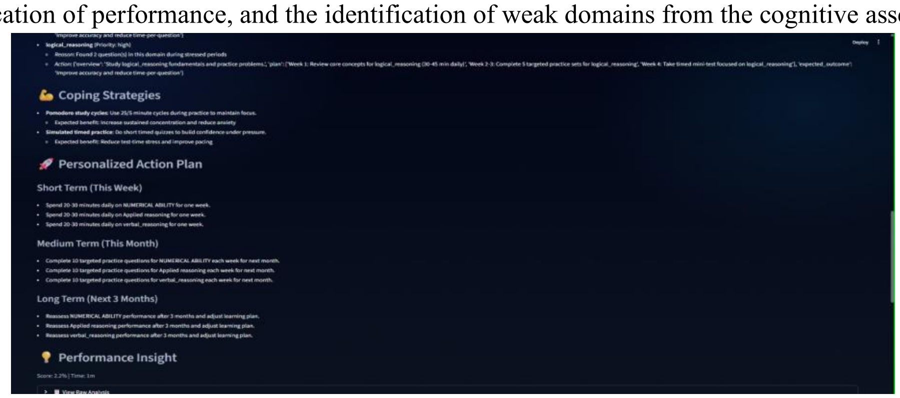

Figure 3. Personalized Recommendation Dashboard

Based on the cognitive performance, stress level, and identified weak domains, the personalized learning and stress-management recommendations generated by the FLAN-T5 Large Transformer model are shown in Figure 3.

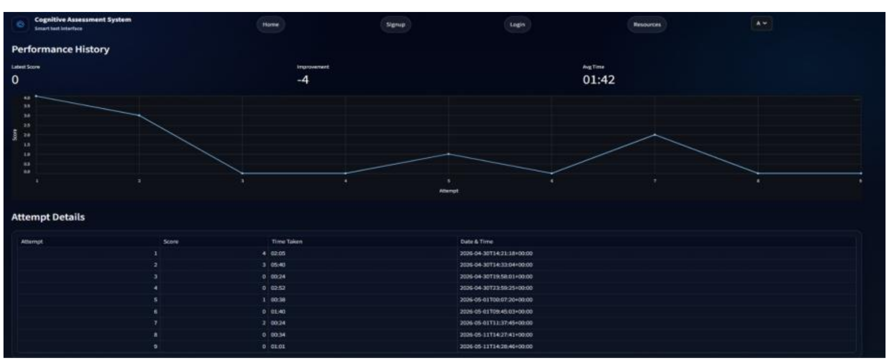

Figure 4. Student Performance History

The assessment history as displayed in Figure 4. shows assessment scores and completion time for each attempt, allowing for performance tracking and progress monitoring over time

The findings reveal that the proposed system has been able to integrate cognitive assessment, physiological monitoring of stress, machine learning analysis and AI recommendation generation as successfully as it has (Islam Ovi et al., 2025; Chung et al., 2024). The system integrates the cognitive score, response time, heart rate and heart rate variability to gain a more holistic perspective of student performance (Kim et al., 2018; Shaffer & Ginsberg, 2017) and to identify some cognitive domains that are underdeveloped and need to be improved.

4. CONCLUSION

The proposed Cognitive Stress Monitoring and Learning Support System integrates cognitive assessment, stress analysis, machine learning and AI Recommendations into a single system. The system assesses the student in five cognitive areas, determines the weak learning areas and monitors the stress level by physiological indicators. The findings demonstrate the potential for using the combination of cognitive performance analysis and stress monitoring to improve learning outcomes and well-being for students. The effectiveness of systems can be further improved by using larger sets of data, more sophisticated sensing technologies and adaptive assessment techniques to create a more effective future system.

Author Declaration

The authors have verified this article is an original work and it is not under consideration for publication in another journal. All sources have been appropriately acknowledged and cited. The authors declare no conflicts of interest with respect to this research, and the manuscript is approved by all the authors.

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