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# MODELLING ACADEMIC BEHAVIOUR AND MENTAL HEALTH USING FUZZY COGNITIVE MAPS WITH SOFT COMPUTING ENHANCEMENTS

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**Abstract**
University students' academic performance and mental health are increasingly understood as tightly linked, especially in Indian higher education, where sustained academic pressure, competitive cultures, and socio-familial expectations place substantial demands on learners. Conventional statistical and machine learning methods often have difficulty capturing the nonlinear, uncertain, and causal relationships that characterise academic and psychological processes. This work introduces a hybrid modelling approach that uses Fuzzy Cognitive Maps (FCMs) together with a set of soft computing methods to capture and project patterns in students' academic behaviours and mental health status. In the model, central academic, behavioural, and psychosocial determinants are encoded as nodes within a connected cognitive network, while the strengths and directions of causal influences between them are automatically adjusted through neuro-fuzzy learning procedures and evolutionary optimisation algorithms. In comparative evaluations, the resulting framework offers better interpretability, flexibility to new data, and predictive reliability than conventional FCM formulations or individual machine learning classifiers used in isolation. Results suggest that the framework is suitable for early identification of at-risk students and can inform academic counselling and institutional decision-making.
**Keywords:** Fuzzy Cognitive Maps, Soft Computing, Student Mental Health, Academic Behaviour, Educational Data Mining.

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## 1. Introduction

Academic behaviour and mental health are central to students' success, persistence, and long-term development in higher education. In many higher-education settings, there has been a noticeable escalation in students' psychological distress, including stress, anxiety, and burnout, linked to intensive coursework, constant online engagement, peer and societal pressures, and worries about employment prospects. These pressures are particularly acute in India, where educational success is strongly associated with upward mobility and fulfilling family aspirations. Conventional quantitative tools such as regression, factor analysis, and structural equation models have been extensively used to investigate academic outcomes and student well-being, yet they usually rely on linearity assumptions and are poorly suited to representing uncertainty, feedback processes, and complex causal networks spanning psychological, behavioural, and academic factors. As a result, their capacity to explain and predict real-world educational dynamics is constrained. Soft computing techniques provide a promising alternative for handling such complexity, as they are designed to tolerate vagueness, partial truth, and ambiguity. Within this paradigm, Fuzzy Cognitive Maps offer a transparent, graph-based representation in which key determinants are modelled as nodes and the causal relationships among them are captured through weighted connections. At the same time, conventional FCMs frequently depend on expert-assigned weights and have restricted learning capabilities, which limits scalability and objectivity.

To overcome these challenges, this work introduces an upgraded FCM-based framework that couples neuro-fuzzy learning with evolutionary optimization to automatically adjust connection weights. By fusing domain-expert input with patterns extracted from data, the approach is designed to boost predictive performance, lessen reliance on subjective manual tuning, and still preserve a transparent, interpretable structure for modelling students' academic behaviour and mental health.

## 2. Literature Review

### 2.1 Student Mental Health Analytics

Student mental health has become a prominent topic in educational data mining and learning analytics. Prior work repeatedly identifies academic stress, workload, family environment, sleep quality, and peer relationships as major determinants of psychological well-being. Data in this domain are typically collected through surveys and psychometric instruments. While machine learning models have achieved encouraging predictive performance, many rely on static datasets and therefore adapt poorly to evolving behavioural patterns. Moreover, a substantial portion of the literature focuses on predicting outcomes rather than understanding causal mechanisms, which restricts the usefulness of these models for designing targeted interventions and counselling strategies.

### 2.2 Academic Behaviour Modelling

Academic behaviour spans multiple dimensions, including attendance, study routines, class participation, motivation, and assessment outcomes. Predictive models based on support vector machines, random forests, neural networks, and recurrent architectures such as LSTMs have been used extensively to detect dropout risk and academic decline. Despite strong predictive power, these models are frequently criticised for limited transparency and explainability. In educational settings, where stakeholders require clear justifications for decisions, purely data-driven "black-box" approaches may not adequately reveal the mechanisms underlying student behaviour.

### 2.3 Fuzzy Cognitive Maps in Behavioural Systems

Fuzzy Cognitive Maps have been applied in healthcare, social sciences, and decision-support applications because they can model rich causal structures in an interpretable way. In behavioural contexts, FCMs allow domain experts to encode feedback loops and interdependencies among relevant factors explicitly. However, traditional FCM implementations depend heavily on expert-specified weights, introducing subjectivity and making large-scale deployment difficult. Static weight matrices also reduce the model's capacity to adapt to new data and changing patterns.

### 2.4 Soft Computing Enhancements to FCMs

Recent work has investigated integrating soft computing techniques—such as neuro-fuzzy learning, genetic algorithms, and particle swarm optimisation—into FCMs to improve learning and performance. These hybrid approaches automatically adjust connection weights, reduce expert bias, and enhance predictive stability. Nonetheless, relatively few studies have addressed the joint modelling of academic behaviour and mental health using such soft-computing-enhanced FCM frameworks. The present work addresses this gap by proposing an integrated, adaptive model that simultaneously captures academic and psychological dimensions.

## 3. Methodology

The proposed framework employs a hybrid strategy that combines expert knowledge with data-driven optimisation. Academic indicators (e.g., grades, attendance, and engagement) are combined with psychological and behavioural variables such as stress, motivation, emotional well-being, sleep quality, and family support. Initial causal links among these factors are specified using expert judgement and prior empirical findings, and encoded as weighted edges in an FCM.

Subsequently, neuro-fuzzy learning procedures iteratively update the connection weights based on observed data patterns. To further strengthen predictive performance and minimise subjectivity, evolutionary optimisation algorithms are applied to refine the weight matrix. Iterative learning continues until convergence criteria are met, yielding an adaptive and stable cognitive map capable of representing complex dynamics linking academic behaviour and mental health.

### 3.1 Sample Size and Population

- **Total Participants:** 520 undergraduate students
- **Institutions:** 3 affiliated colleges under University of Mumbai
- **Age Range:** 18–23 years
- **Gender Distribution:**
  - Male: 54%
  - Female: 45%
  - Other: 1%
- **Academic Streams:** Arts, Commerce, Science, IT

The dataset was collected during two academic semesters (2024–2025) to ensure temporal stability.

### 3.2 Data Source

Data was collected from:

1. **Institutional Academic Records**
   - GPA / Semester Percentage
   - Attendance (%)
   - Assignment submission rate
   - Internal assessment marks
2. **Standardized Psychometric Surveys**
   - Perceived Stress Scale (PSS)
   - Generalized Anxiety Scale (GAD-7)
   - Sleep Quality Index
   - Motivation Scale
   - Emotional Well-Being Index
3. **Structured Behavioural Questionnaire**
   - Screen time
   - Study hours per day
   - Peer interaction score
   - Family support index

Ethical approval was obtained and responses were anonymized.

### 3.3 Input Variables (FCM Nodes)

| Category | Variables |
|---|---|
| Academic | Grades, Attendance, Engagement |
| Psychological | Stress, Anxiety, Emotional Well-being |
| Behavioural | Sleep Quality, Study Hours, Screen Time |
| Social | Family Support, Peer Interaction |
| Output | Mental Health Risk Index |

### 3.4 Preprocessing Steps

**Step 1: Data Cleaning**

- Missing values (<5%) → Imputed using mean/mode.
- Outliers → Detected via IQR method and Winsorized.

**Step 2: Normalization**

All numerical features were scaled to [0,1] using Min-Max normalization:

$X' = (X - X_{min}) / (X_{max} - X_{min})$

**Step 3: Fuzzification**

Continuous variables were converted into linguistic categories:

- Low
- Moderate
- High

Triangular membership functions were used.

**Step 4: Feature Selection**

Correlation analysis and mutual information were used to remove redundant predictors.

**Step 5: Train-Test Split**

- 70% Training
- 30% Testing
- 5-fold Cross Validation applied

## 4. Results and Discussion

Experimental analyses show that the soft-computing-enhanced FCM delivers higher predictive accuracy and stability than traditional FCMs and standard machine learning classifiers. The model captures nonlinear interactions and feedback mechanisms that are often missed by linear analytical approaches. Examination of causal influences indicates that heavy academic workload, insufficient sleep, and elevated stress have strong negative impacts on mental health, whereas peer interaction, emotional resilience, and family support play moderating and protective roles. Because the cognitive map structure is interpretable, these relationships can be examined in a way that is useful for counselling services and institutional support systems.

### 4.1 Classification Performance (Mental Health Risk Prediction)

The proposed Neuro-Fuzzy + Evolutionary Optimized FCM was compared with:

- Traditional FCM (Expert-defined weights)
- Random Forest
- Support Vector Machine
- Artificial Neural Network (MLP)

| Model | Accuracy | Precision | Recall | F1-Score | AUC |
|---|---|---|---|---|---|
| **Traditional FCM** | **78.4%** | **0.76** | **0.74** | **0.75** | **0.80** |
| **Random Forest** | **84.9%** | **0.83** | **0.82** | **0.82** | **0.88** |
| **SVM** | **82.1%** | **0.80** | **0.79** | **0.79** | **0.85** |
| **ANN (MLP)** | **86.3%** | **0.85** | **0.84** | **0.84** | **0.90** |
| **Proposed Hybrid FCM** | **90.7%** | **0.89** | **0.88** | **0.88** | **0.93** |

## 5. Conclusion

This study introduces an interpretable and adaptive framework for modelling academic behaviour and mental health using Fuzzy Cognitive Maps enhanced with soft computing techniques. By fusing expert insight with automated learning and optimisation, the framework overcomes key drawbacks of classical FCMs and opaque machine learning models. It aligns with the needs of Indian higher education institutions by enabling early identification of vulnerable students and supporting evidence-based academic interventions. Future extensions could incorporate real-time learning analytics, larger longitudinal datasets, and additional explainable AI methods to further strengthen transparency and decision support.

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