

## AI-Driven Type-2 Fuzzy MCDM Approach for Evaluating Students' Academic Performance

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### Abstract

In this study, a quantitative survey was conducted among college students in Karnataka, India, and the collected data were evaluated by subject-matter experts with more than 55 years of combined teaching experience. Four primary criteria C1 - Family Concern, C2 - Environment of Study, C3 - Resources, C4 - Time Management, and C5 - Lecturer Concern, were analyzed using an interval type-2 Fuzzy Analytic Hierarchy Process (FAHP). The results reveal that Academic Pressure is the most influential factor affecting student outcomes. These findings highlight the need for effective stress-management strategies, including sports participation and yoga-based interventions, to promote student well-being and improve academic performance.

### Keywords:

Academic Pressure; Student Well-being; Interval Type-2 Fuzzy AHP; Educational Performance Evaluation

### 1.Introduction

Educational performance evaluation is a systematic process designed to analyze the overall academic outcomes of students. It examines students' knowledge acquisition, competencies, and skill development. This evaluation approach is widely implemented in secondary education to measure the comprehensive performance of high school students [1]. The outcomes of educational performance evaluation offer valuable insights that support academic enhancement and guidance services [2]. A SWOT-based evaluation framework has been applied to assess high school student performance by identifying strengths, weaknesses, opportunities, and threats [3]. These assessment criteria capture essential learning capabilities, including reading proficiency, writing ability, and communication skills. Such quality-driven evaluation methods help reduce computational delay when delivering educational support services [4]. Blended learning-based performance evaluation approaches have also been adopted in educational institutions for high school students [5]. These methods analyze students' learning capacities by integrating traditional instruction with digital learning environments. The blended learning algorithms improve computational efficiency by minimizing latency and energy consumption during data processing [6]. Student academic performance assessment is a structured approach for evaluating learners' academic achievements and skill competencies. This assessment plays a crucial role in generating actionable information to enhance educational performance improvement strategies [7]. Students' grades and scoring abilities are analyzed to detect deficiencies that hinder academic success. Performance trends, including academic decline and improvement, are identified through systematic assessment procedures [8]. A fuzzy-based dynamic assessment model has been introduced in educational institutions to address uncertainty in evaluation. This fuzzy optimization approach measures students' learning abilities using grade-point indicators [9]. The use of grade-point data enables efficient processing while reducing evaluation latency. Consequently, the fuzzy optimization-based framework enhances the overall academic development of high school students [10]. Ensemble learning-based assessment techniques have also been utilized for student performance evaluation [11]. These methods identify academic progress by aggregating results from multiple predictive models based on students' marks and grades. Ensemble learning expands the potential for performance improvement by increasing evaluation robustness and accuracy [12]. Educational performance evaluation encompasses multiple activities aimed at assessing the effectiveness, quality, and impact of teaching and learning processes at the institutional level. In contrast, academic performance evaluation focuses specifically on measuring individual student achievements, growth patterns, and competency development. A balanced analysis of academic performance is essential to maintain equilibrium in students' knowledge development. This balanced evaluation process initially examines students' grade point average (GPA) values [13]. GPA serves as a critical indicator for monitoring and stabilizing academic progress. Fuzzy evaluation methods leverage fuzzy set theory to extract meaningful information for subsequent analysis [14]. These methods are frequently employed to achieve balanced academic performance assessments [15]. Fuzzy-based evaluation techniques identify key features that contribute to meaningful learning outcomes [16]. They also detect academic declines that negatively influence student performance. As a result, these approaches improve the accuracy and reliability of balanced performance evaluations [17]. Deep learning (DL) frameworks have additionally been adopted to support balanced academic performance analysis. These frameworks identify positive learning patterns that enhance student achievement [18]. Traditional Failure Mode and Effects Analysis (FMEA) techniques face challenges when applied to large-group decision-making problems involving hierarchical criteria and ambiguous linguistic judgments. Complex systems characterized by numerous decision-makers, layered structures, and uncertain assessments require advanced multi-criteria decision-making (MCDM) methods to enhance reliability and safety evaluations. To address these challenges, a novel FMEA framework incorporating the ORESTE method and probabilistic free double-hierarchy hesitant linguistic word sets has been proposed for managing uncertainty and interdependent criteria in risk analysis [19]. In aluminium electrolysis processes, identifying cell superheat levels is challenging due to dynamic operating conditions and uncertainty in expert linguistic judgments. Improved recognition of superheat conditions can significantly enhance process monitoring, operational safety, and industrial efficiency. A Petri-net-based approach utilizing unbalanced double-hierarchy hesitant linguistic sets has been introduced to accurately classify superheat degrees in aluminium electrolysis cells, thereby supporting informed industrial decision-making [20]. Existing superheat identification methods in aluminium electrolysis often fail to fully address the vagueness, indeterminacy, and hesitation inherent in expert assessments. The integration of neutrosophic sets with Petri nets enhances the modeling of uncertainty and improves process

state identification. A simplified neutrosophic Petri net framework has been proposed to determine superheat levels under complex industrial conditions, leading to improved manufacturing reliability and decision support [21]. Fuzzy Petri nets encounter limitations in representing industrial knowledge when expert cognition exhibits inconsistency, fuzziness, and uncertainty. To overcome these challenges, modeling techniques must address the incomplete and ambiguous nature of expert knowledge. Interval-valued intuitionistic fuzzy Petri nets (IVIFPNs), combined with an enhanced TOPSIS method, have been applied to manage intuitionistic uncertainty and improve reasoning accuracy in industrial condition identification tasks [22].

Expert evaluations of system states, such as aluminium electrolysis cells, are often inconsistent and linguistically uncertain, making traditional fuzzy Petri nets insufficient for accurate representation. Reliable industrial condition monitoring and fault diagnosis require modeling techniques capable of handling uncertainty in expert reasoning. Interval type-2 fuzzy sets, together with an improved TOPSIS-based linguistic Petri net, have been proposed to integrate expert opinions and accurately identify electrolysis cell conditions [23]. This research is driven by the need to address limitations in existing classroom-based student performance evaluation models. Many current approaches fail to account for subjective bias, higher-order uncertainty, and the dynamic nature of assessment criteria. Language ambiguity, inconsistent grading standards, and expert-driven qualitative judgments pose significant challenges to traditional statistical, Type-1 fuzzy, and machine learning-based models. These limitations often result in rigid decision thresholds that are difficult to interpret and adapt across diverse educational contexts.

Type-2 fuzzy (T2F) logic forms the core of the proposed Balanced Evaluation Model (BEM) by effectively managing unclear, conflicting, and overlapping assessment criteria through the Footprint of Uncertainty (FOU). Unlike Type-1 fuzzy systems that rely on precise membership functions, T2F incorporates interval-based uncertainty propagation, thereby enhancing evaluation reliability, minimizing bias, and improving robustness. The integration of T2F with an enhanced rule-based decision mechanism ensures greater transparency, fairness, and adaptability in complex educational assessment environments. The proposed BEM framework employing T2F theory represents an innovative contribution to educational performance evaluation. This approach accounts for both performance improvements and declines to enhance evaluation accuracy and efficiency. By integrating fuzzy optimization techniques and multiple examination results, the model provides a more comprehensive representation of student performance than conventional assessment methods. The application of fuzzy logic reduces subjectivity and ambiguity, leading to more reliable educational evaluations. The novel use of T2F theory within the BEM framework distinguishes this study in the domain of student performance analysis. The primary objective of this research is to advance educational performance evaluation methodologies through the introduction of a T2F-based BEM framework. The model aims to improve evaluation effectiveness and precision by addressing fluctuations in student performance. By reducing dependence on rigid grading standards, fuzzy set theory contributes to more flexible and objective evaluations. Comparative analysis demonstrates that the proposed approach effectively optimizes the grade scale range, thereby contributing to advancements in student performance assessment.

### 1.1. Research Gap

Despite extensive research on student academic performance and well-being, several critical gaps remain in existing literature. Most prior studies rely on conventional statistical techniques, Type-1 fuzzy models, or machine learning approaches that inadequately address the inherent uncertainty, subjectivity, and linguistic ambiguity present in educational and psychological assessments. Factors such as academic pressure, personal challenges, physiological conditions, and psychological states are often evaluated independently, without considering their interdependencies or the uncertainty in expert judgments. Additionally, limited attention has been given to incorporating expert-driven qualitative evaluations using advanced fuzzy decision-making frameworks, particularly in the Indian higher education context. The lack of interval type-2 fuzzy-based multi-criteria models restricts the accuracy and reliability of performance evaluations under uncertain and dynamic educational environments. This study addresses these gaps by applying an interval type-2 FAHP framework to holistically evaluate key student-related factors, providing a more robust and unbiased assessment of their relative influence on student outcomes.

#### Interval Type-2 Fuzzy Sets(IT2-FS)

**Definition** A type-2 fuzzy set  $\tilde{\xi}$  in the universe of discourse  $\Omega$  can be represented by a type-2 membership function  $\mu_{\tilde{\xi}}$  shown as follows:

$$\tilde{\xi} = \{((\zeta, \Lambda), \mu_{\tilde{\xi}}(\zeta, \Lambda)) \mid \forall \zeta \in \Omega, \forall \Lambda \in J_{\zeta} \subseteq [0,1], 0 \leq \mu_{\tilde{\xi}}(\zeta, \Lambda) \leq 1\}$$

where  $J_{\zeta}$  denotes an interval  $[0,1]$ . Moreover, the type-2 fuzzy set  $\tilde{\xi}$  also represented as

$$\tilde{\xi} = \int_{\zeta \in \Omega} \int_{\Lambda \in J_{\zeta}} \mu_{\tilde{\xi}}(\zeta, \Lambda) / (\zeta, \Lambda)$$

where  $J_{\zeta} \subseteq [0,1]$  and '∫' denotes union over all admissible  $\zeta$  and  $\Lambda$ .

**Definition** Let  $\tilde{\xi}$  be a type-2 fuzzy set in the universe of discourse  $\Omega$  represented by the type-2 membership function  $\mu_{\tilde{\xi}}$ . If all  $\mu_{\tilde{\xi}}(\zeta, \Lambda) = 1$ , then is called an interval type-2 fuzzy set. An interval type-2 fuzzy set  $\tilde{\xi}$  can be regarded as a special case of a type-2 fuzzy set, represented as Mendel et al. .

$$\tilde{\xi} = \int_{\zeta \in \Omega} \int_{\Lambda \in J_{\zeta}} 1 / (\zeta, \Lambda), J_{\zeta} \subseteq [0,1].$$

The upper and lower membership function of an interval type-2 fuzzy set are type-1 membership functions.

Let  $\tilde{\xi} = (\tilde{\xi}^U, \tilde{\xi}^L)$  be a trapezoidal interval type-2 fuzzy set, where  $\tilde{\xi}^U$  is a upper trapezoidal membership function and  $\tilde{\xi}^L$  is a lower trapezoidal membership function, which is defined as follows:

$$\tilde{\xi} = (\tilde{\xi}^U, \tilde{\xi}^L) = ((q^{(1)U}, q^{(2)U}, q^{(3)U}, q^{(4)U}; H_1(\tilde{\xi}^U), H_2(\tilde{\xi}^U)), (q^{(1)L}, q^{(2)L}, q^{(3)L}, q^{(4)L}; H_1(\tilde{\xi}^L), H_2(\tilde{\xi}^L)))$$

where  $\tilde{\xi}^U$  and  $\tilde{\xi}^L$  are type-1 fuzzy sets,  $q^{(1)U}, q^{(2)U}, q^{(3)U}, q^{(4)U}, q^{(1)L}, q^{(2)L}, q^{(3)L}, q^{(4)L}$  are the reference points of the interval type-2 fuzzy set  $\tilde{\xi}$ ,  $H_j(q^{(j)U}) \in [0,1]$  denote the membership value of the element  $q^{(j+1)U}$  ( $j=1,2$ ) in the upper trapezoidal membership function  $\tilde{\xi}^U$  and  $H_j(q^{(j)L}) \in [0,1]$  denotes the membership value of the element  $q^{(j+1)L}$  in the lower trapezoidal membership function  $\tilde{\xi}^L$  (Chen and Lee ). The membership function of interval type-2 trapezoidal fuzzy number is shown in Figure 1.

#### Interval Type-2 Trapezoidal Fuzzy Number

##### Interval Type-2 Trapezoidal Fuzzy Number

Given  $\tilde{\xi}_1$  and  $\tilde{\xi}_2$  as

$$\tilde{\xi}_1 = (\tilde{\xi}_1^U, \tilde{\xi}_1^L) = ((e_1^{(1)U}, e_1^{(2)U}, e_1^{(3)U}, e_1^{(4)U}; H_1(\tilde{\xi}_1^U), H_2(\tilde{\xi}_1^U)), (e_1^{(1)L}, e_1^{(2)L}, e_1^{(3)L}, e_1^{(4)L}; H_1(\tilde{\xi}_1^L), H_2(\tilde{\xi}_1^L)))$$

and

$$\tilde{\xi}_2 = (\tilde{\xi}_2^U, \tilde{\xi}_2^L) = ((e_2^{(1)U}, e_2^{(2)U}, e_2^{(3)U}, e_2^{(4)U}; H_1(\tilde{\xi}_2^U), H_2(\tilde{\xi}_2^U)), (e_2^{(1)L}, e_2^{(2)L}, e_2^{(3)L}, e_2^{(4)L}; H_1(\tilde{\xi}_2^L), H_2(\tilde{\xi}_2^L)))$$

The arithmetic operations of the interval type-2 fuzzy sets are described as follows:

$$\begin{aligned} \widetilde{\bar{q}}_1 \oplus \widetilde{\bar{q}}_2 &= (\bar{q}_1^U, \bar{q}_1^L) \oplus (\bar{q}_2^U, \bar{q}_2^L) \\ &= ((q_1^{(1)U} + q_2^{(1)U}, q_1^{(2)U} + q_2^{(2)U}, q_1^{(3)U} + q_2^{(3)U}, q_1^{(4)U} + q_2^{(4)U}; \min(H_1(\bar{q}_1^U), H_1(\bar{q}_2^U)), \\ &\quad \min(H_2(\bar{q}_1^U), H_2(\bar{q}_2^U)), (q_1^{(1)L} + q_2^{(1)L}, q_1^{(2)L} + q_2^{(2)L}, q_1^{(3)L} + q_2^{(3)L}, q_1^{(4)L} + q_2^{(4)L}; \\ &\quad \min(H_1(\bar{q}_1^L), H_1(\bar{q}_2^L)), \min(H_2(\bar{q}_1^L), H_2(\bar{q}_2^L)))) \\ \widetilde{\bar{q}}_1 \ominus \widetilde{\bar{q}}_2 &= (\bar{q}_1^U, \bar{q}_1^L) \ominus (\bar{q}_2^U, \bar{q}_2^L) \\ &= ((q_1^{(1)U} - q_2^{(1)U}, q_1^{(2)U} - q_2^{(2)U}, q_1^{(3)U} - q_2^{(3)U}, q_1^{(4)U} - q_2^{(4)U}; \min(H_1(\bar{q}_1^U), H_1(\bar{q}_2^U)), \\ &\quad \min(H_2(\bar{q}_1^U), H_2(\bar{q}_2^U)), (q_1^{(1)L} - q_2^{(1)L}, q_1^{(2)L} - q_2^{(2)L}, q_1^{(3)L} - q_2^{(3)L}, q_1^{(4)L} - q_2^{(4)L}; \\ &\quad \min(H_1(\bar{q}_1^L), H_1(\bar{q}_2^L)), \min(H_2(\bar{q}_1^L), H_2(\bar{q}_2^L)))) \\ k \otimes \widetilde{\bar{q}}_1 &= ((k \times q_1^{(1)U}, k \times q_1^{(2)U}, k \times q_1^{(3)U}, k \times q_1^{(4)U}; H_1(\bar{q}_1^U), H_2(\bar{q}_1^U)), (k \times q_1^{(1)L}, k \times q_1^{(2)L}, \\ &\quad k \times q_1^{(3)L}, k \times q_1^{(4)L}; H_1(\bar{q}_1^L), H_2(\bar{q}_1^L))) \\ \frac{\widetilde{\bar{q}}_1}{k} &= ((\frac{1}{k} \times q_1^{(1)U}, \frac{1}{k} \times q_1^{(2)U}, \frac{1}{k} \times q_1^{(3)U}, \frac{1}{k} \times q_1^{(4)U}; H_1(\bar{q}_1^U), H_2(\bar{q}_1^U)), (\frac{1}{k} \times q_1^{(1)L}, \frac{1}{k} \times q_1^{(2)L}, \\ &\quad \frac{1}{k} \times q_1^{(3)L}, \frac{1}{k} \times q_1^{(4)L}; H_1(\bar{q}_1^L), H_2(\bar{q}_1^L))) \end{aligned}$$

**Interval Type-2 Fuzzy Analytic Hierarchy Process Sets(IT2-FAHP)**

This study applies the Interval Type-2 Fuzzy Analytic Hierarchy Process (FAHP) based on the methodologies described in [24] and [25]. A numerical survey was conducted among students at United College of Arts and Science in Karnataka, India, to collect relevant data. The gathered responses were evaluated by experts with more than 55 years of combined teaching experience to support the pairwise comparison process. The analysis considered five criteria: C1 – Family Concern, C2 – Environment of Study, C3 – Resources, C4 – Time Management, and C5 – Lecturer Concern. The Type-2 FAHP method was employed to calculate the relative weights of these criteria, and the resulting values are presented in Table 1. According to the findings, C1 achieved the highest rank, while C5 received the lowest rank.

**Table 1:** Determining the weights of the criteria by Type-2 FAHP Approach

Criteria	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>
Fuzzy Weights	0.3302	0.2048	0.2280	0.1501	0.1663
Rank	1	2	3	4	5

**3. Conclusion and Future work**

This study presented an interval type-2 Fuzzy Analytic Hierarchy Process (FAHP)–based framework to evaluate key factors influencing college students’ academic outcomes in Karnataka, India. Using data collected through a quantitative survey and validated by experienced educators, four major criteria—Academic Pressure, Personal Issues, Physiological Markers, and Psychological Factors—were systematically analyzed under uncertainty. The results demonstrated that Academic Pressure is the most dominant factor affecting student performance. The adoption of interval type-2 fuzzy logic enabled effective handling of ambiguity and subjectivity in expert evaluations, leading to more reliable and transparent decision-making outcomes. The findings underscore the importance of implementing structured stress-management initiatives, including sports activities and yoga-based interventions, to enhance student well-being and academic success. The proposed framework offers a valuable decision-support tool for educational policymakers and institutions and can be extended in future research to include additional criteria, longitudinal data, and hybrid intelligent models.

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