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Adaptive Multi-Stage Fuzzy Logic Model of Student Knowledge Assessment

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Abstract: Accurate and objective assessment of students' knowledge remains a challenging problem due to the inherent uncertainty and subjectivity of traditional evaluation systems. Conventional grading approaches often fail to account for task complexity, discrimination power, and variability in student responses, which leads to inconsistent and biased results. This study proposes a multi-stage fuzzy logic–based decision-making model for knowledge assessment. The model integrates several key evaluation indicators, including task difficulty, discrimination index, response value, and response weight, within a unified fuzzy inference framework. A structured multi-factor evaluation mechanism is developed, where fuzzy membership functions and rule-based inference are used to transform qualitative judgments into quantitative assessment measures. Furthermore, a defuzzification process based on the Center of Gravity (COG) method is applied to obtain final scores, and a correction mechanism is introduced to refine evaluation outcomes. A comparative analysis was conducted using assessment data from 100 students across 5 tasks evaluated on a [0–10] scale. The results suggest that the proposed approach provides a more differentiated and consistent interpretation of student performance than the traditional assessment method. The proposed model provides a reliable and interpretable framework for evaluating students' knowledge and supports the development of adaptive and intelligent educational assessment systems.

Index Terms: Fuzzy Sets, Educational System, Students Knowledge, Assessment System, Objectivity, Differentiation Index, Response Value, Fuzzification, Logical Control, Educational Effectiveness, Innovative Methods, Dynamic Assessment, Individualized Approach, Students' Success

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1. Introduction

Assessment of students' knowledge and skills plays an important role in the educational process. In practice, however, traditional evaluation methods are often influenced by subjective judgment and do not always reflect the actual level of students' understanding. As a result, students who receive the same grade may differ significantly in their knowledge, reasoning ability, and task performance. This situation indicates the need for more objective, transparent, and reliable assessment approaches. A well-organized assessment system can improve the effectiveness of the learning process and provide more consistent evaluation results [1, 2].

In recent years, various intelligent methods have been applied to improve the quality of educational assessment systems. In particular, fuzzy set theory, introduced by Zadeh, has been widely used to model uncertainty in complex decision-making processes [3]. The main advantage of fuzzy logic is that it allows the use of linguistic and approximate values, which makes it suitable for educational evaluation where strict numerical boundaries are often difficult to define [3, 4]. In addition to classical fuzzy decision models, recent studies have shown that intelligent assessment systems increasingly combine flexible rule-based reasoning, adaptive learning mechanisms, and data-driven evaluation strategies in order to support more balanced interpretation of student performance [5–7].

A growing body of research has explored fuzzy and intelligent methods in educational assessment. These studies indicate that fuzzy logic, adaptive assessment, and knowledge-based models can improve the flexibility and consistency of academic evaluation. However, the development of an interpretable multi-factor assessment framework that jointly considers task difficulty, discrimination capability, response value, and response weight remains an open research issue. Therefore, the next section reviews related studies in intelligent and fuzzy logic-based educational assessment.

1.1. Problem Statement

Although a number of studies have explored fuzzy logic and intelligent assessment in education, several limitations remain. First, many traditional assessment systems still rely mainly on direct scoring and rigid grade boundaries, which may fail to capture the actual complexity of student performance across different tasks [8, 10, 11]. Second, even when intelligent or fuzzy approaches are applied, some models focus only on a limited number of evaluation criteria and do not fully account for the interaction among task difficulty, discrimination capability, response quality, and response importance [9, 12–15]. As a result, the obtained evaluation may still remain sensitive to simplification and may not fully represent the multidimensional nature of student knowledge.

Another important issue is that students with similar total scores may demonstrate substantially different levels of understanding at the task level. This makes it difficult for conventional systems to provide a sufficiently balanced interpretation of learning outcomes. Recent works on fuzzy performance evaluation, adaptive assessment, and intelligent educational systems emphasize the importance of integrating several indicators into a unified evaluation procedure rather than relying on a single aggregated score [16–22]. Therefore, there is still a need for an interpretable assessment model that can combine multiple evaluation indicators in a structured way and reduce subjectivity in the final decision-making process.

1.2. Research Motivation and Contribution

Taking these aspects into account, this study proposes a fuzzy logic-based approach for assessing students' knowledge using multiple evaluation indicators. The model considers task difficulty, discrimination index, response value, and response weight, and combines them within a unified multi-stage assessment framework. The proposed approach is intended to reduce subjectivity in assessment and to provide more consistent evaluation results.

In addition, the model includes a correction mechanism that helps improve the consistency of the final evaluation results. From a practical point of view, the proposed framework can support instructors in making more objective and balanced assessment decisions and can be used as a basis for adaptive educational assessment systems. In this sense, the contribution of the study lies not in the use of fuzzy logic itself, but in the development of a structured multi-factor model that combines several educational evaluation indicators within one interpretable decision-making process.

2. Related Work

Recent studies show that intelligent assessment systems are increasingly being used to improve the objectivity, adaptability, and transparency of educational evaluation. Kuang et al. [2] analyzed the objectives, methods, and challenges of intelligent assessment in education and emphasized that modern assessment systems should not be limited to direct scoring, but should also support meaningful interpretation of learning outcomes. In this direction, knowledge-based and ontology-based approaches have been proposed to represent classroom activities, learning objectives, and assessment criteria in a more structured form [8, 9].

Several studies have focused on adaptive and knowledge-based assessment models. Hatzilygeroudis et al. [12] developed a knowledge-based adaptive assessment approach for web-based intelligent educational systems, showing that assessment can be improved when student responses are interpreted through a rule-based mechanism. Similarly, Wang et al. [11] proposed a unified knowledge tracing framework for subjective and objective assessments, highlighting the need

to consider different types of student responses within a single evaluation structure. These studies indicate that educational assessment should reflect not only the final score, but also the structure and quality of student performance.

Fuzzy logic has also been widely applied in student performance evaluation because it allows uncertain, partial, and linguistically expressed knowledge to be modeled more flexibly. Jan et al. [14] used fuzzy logic to monitor students' academic performance in higher education, demonstrating its usefulness for dealing with uncertainty in academic evaluation. Hu et al. [15] proposed an educational performance evaluation model based on fuzzy evaluation, while Barlybayev et al. [16] conducted a comparative analysis of grading models using fuzzy logic to improve fairness and consistency in student performance evaluation. These works confirm that fuzzy models can provide a more flexible alternative to rigid grading boundaries.

More recent studies have extended fuzzy assessment toward intelligent and adaptive educational environments. Ergin and Nasibov [17] analyzed students' academic performance using a fuzzy inference system, showing that fuzzy rules can support more interpretable evaluation decisions. Yang [21] developed a fuzzy comprehensive evaluation and decision support system for online course learning management, while Karl et al. [22] investigated the use of fuzzy logic and machine learning methods in advanced examination systems. These studies demonstrate the growing importance of intelligent assessment models in digital and adaptive learning environments.

Despite these contributions, existing studies often focus on a limited set of assessment indicators or address student performance mainly from the perspective of general academic achievement. Less attention has been given to the joint consideration of task difficulty, discrimination index, response value, and response weight within one interpretable fuzzy inference framework. Therefore, the present study aims to fill this gap by developing a multi-stage fuzzy logic-based assessment model that integrates these indicators and applies a correction mechanism to obtain more balanced and consistent evaluation results.

3. Proposed Approach

In this study, a fuzzy logic–based approach is employed for assessing students' knowledge. The use of fuzzy logic allows the modeling of uncertainty and ambiguity that naturally arise in educational evaluation processes. Unlike traditional methods, which rely on strict numerical boundaries, fuzzy logic provides a more flexible framework for representing partial knowledge and varying levels of student performance. As a result, it becomes possible to describe evaluation criteria in a way that is closer to real teaching practice.

The fuzzy logic model integrates several parameters and decision rules to achieve more consistent outcomes, thereby simplifying the decision-making process and improving its efficiency. This approach supports a multi-dimensional evaluation mechanism that considers not only final scores but also qualitative aspects of learning. Consequently, it contributes to improving the educational process and provides a more realistic interpretation of students' level of comprehension [4].

The fuzzy control model considers multiple parameters when evaluating students' knowledge. These parameters include:

- **Degree of difficulty** – used to determine the complexity level of the task and its impact on student performance.
- **Discrimination index** – enables analysis of differences among students' responses and helps identify how well a task distinguishes between different knowledge levels.
- **Response value** – serves as a key indicator in assessing whether a student's answer is correct or partially correct.
- **Response weight** – indicates the relative importance of each task within the overall evaluation process.

In addition to these factors, the interaction between different indicators is also taken into account, which allows the model to reflect the real structure of the assessment process more accurately. By combining these parameters within a unified framework, the system produces final decisions that support a more objective evaluation of students' knowledge and skills. The primary objective of the model is to ensure fairness in determining students' comprehension levels and to provide instructors with meaningful insights into students' strengths and weaknesses.

The overall scheme of the assessment process is illustrated in Fig 1, which shows the step-by-step analysis of evaluation criteria and the process of arriving at a final decision. This scheme reflects the logical sequence of data processing, from initial inputs to final evaluation results. Through this approach, a multi-factor assessment method is applied to determine students' knowledge levels, ensuring a comprehensive and systematic evaluation process.

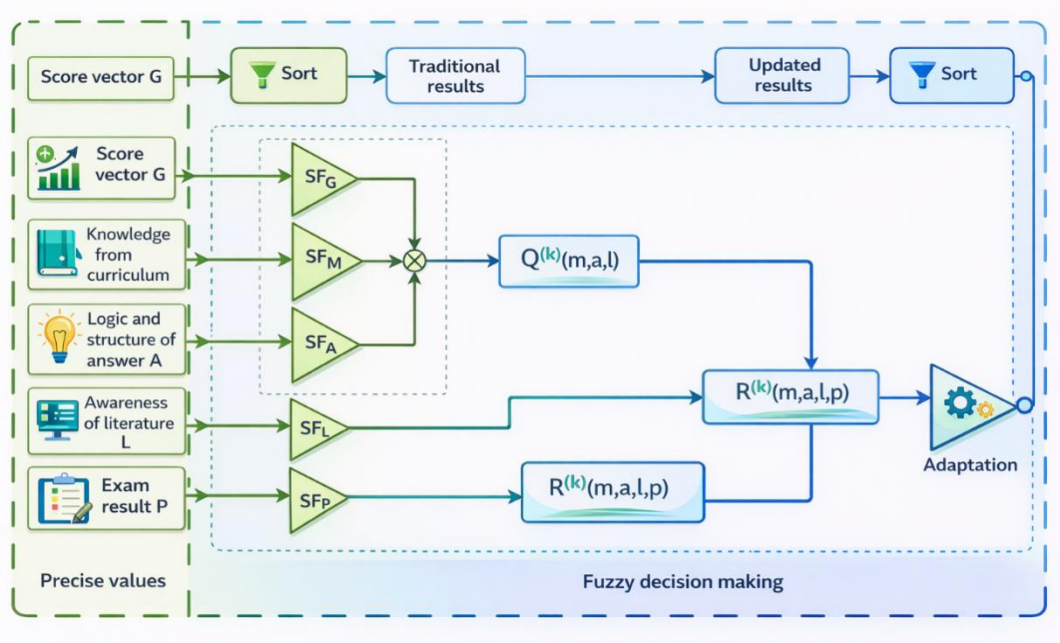


Fig. 1. Decision-making scheme based on multi-factor analysis of learning performance indicators.

This scheme is designed to implement a step-by-step analytical process, where each stage serves as a foundation for ensuring the accuracy of identifying, analyzing, and making decisions based on students' performance indicators. The sequence of these stages is detailed below.

Stage 1. For each task T_i, the student's score $p_{h_{ij}}$ is determined as a value assigned by instructor I_j. Based on the evaluations from all instructors, the final score of each student for each task is calculated using a weighted average. Then, a matrix M is constructed to represent the scores for each task and student as follows:

$$M = \overbrace{\frac{1}{n}\sum_{j=1}^{n} p_{11j}}^{T_1} \overbrace{\frac{1}{n}\sum_{j=1}^{n} p_{12j}}^{T_2} \ldots \overbrace{\frac{1}{n}\sum_{j=1}^{n} p_{1mj}}^{T_n}. \quad (1)$$

For each task T_i (where $1 \le i \le m$), the top 20% of students with the highest scores are selected as the "high group", while the bottom 20% of students with the lowest scores are selected as the "low group". The average scores of each group are then calculated and denoted as $\bar{H}_i$ and $\bar{L}_i$, respectively. The difficulty level of task T_i is then calculated using the following formula:

$$d_i = 1 - \frac{\bar{H}_i + \bar{L}_i}{2q_i}. \quad (2)$$

Where, d_i denotes the difficulty level, and its value lies within the interval $0 \le d_i \le 1$. Each $d_i$is converted into a fuzzy value based on five fuzzy sets, and a membership value is calculated for each set (Fig 2). Based on these parameters, the difficulty matrix D is constructed as follows:

$$D = \begin{matrix} T_1 \\ T_2 \\ \vdots \\ T_m \end{matrix} \begin{pmatrix} \overbrace{d_{11}}^{L} & \overbrace{d_{11}}^{SL} & \overbrace{d_{11}}^{M} & \overbrace{d_{11}}^{SH} & \overbrace{d_{11}}^{H} \\ d_{21} & d_{22} & d_{23} & d_{24} & d_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & d_{m3} & d_{m4} & d_{m5} \end{pmatrix}. \quad (3)$$

Here, $d_{iw} \in [0,1]$ and $1 \le i \le m, 1 \le w \le 5$ represent the membership value of each task T_i corresponding to the five fuzzy sets.

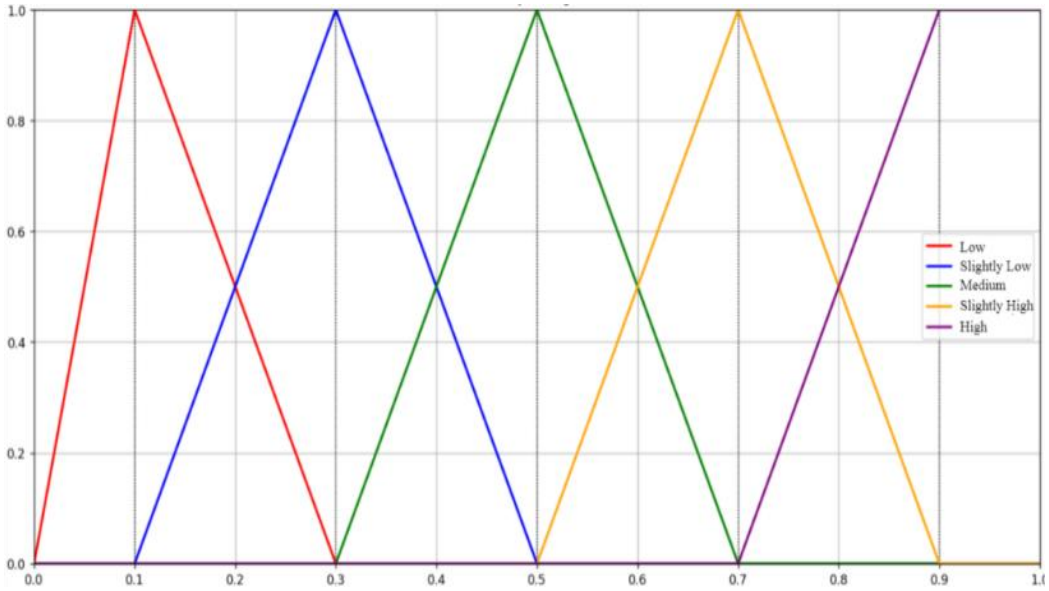


Fig. 2. Membership functions of five fuzzy values

Stage 2. Based on the score matrix M, the membership value of the discrimination index corresponding to each fuzzy set for task T_i is calculated. As a result, the following fuzzy discrimination index matrix is constructed:

$$F = \begin{matrix} T_1 \\ T_2 \\ \vdots \\ T_m \end{matrix} \begin{pmatrix} \overbrace{f_{11}}^{L} & \overbrace{f_{12}}^{LM} & \overbrace{f_{13}}^{M} & \overbrace{f_{14}}^{SH} & \overbrace{f_{15}}^{H} \\ f_{21} & f_{22} & f_{23} & f_{24} & f_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ f_{m1} & f_{m2} & f_{m3} & f_{m4} & f_{m5} \end{pmatrix}. \quad (4)$$

Where:

$$f_{iw} \in [0,1] \ (where \quad 1 \le i \le m, 1 \le w \le 5)$$

represents the membership value of the discrimination index of task T_i corresponding to the five fuzzy sets related to the i-th task.

During this process, the discrimination indices of the tasks reflect the differences in student performance levels and enhance the accuracy and consistency of evaluation through fuzzy values. This system enables both instructors and students to identify disparities in the assessment process.

Stage 3. A set of rules for fuzzy logical inference R_A – is developed (Table 1). This rule set is applied together with the fuzzy difficulty matrix D and the fuzzy discrimination index matrix F to perform fuzzy inference in evaluating the response value of each task.

Table 1. Fuzzy inference rules RA (RE) used to determine the evaluation indicators of the response

Fuzzy Discrimination Index	**Fuzzy Complexity**				
	L	SL	M	SH	H
L	L	P	SL	SL	M
SL	L	SL	SL	M	SH
M	SL	SL	M	SH	SH
SH	SL	M	SH	SH	H
H	M	SH	SH	H	H

In fuzzy inference rules, the discrimination index and difficulty level are used respectively as the evaluation value of the response and the assessment weight calculated through fuzzy rules. In other words, complexity and discrimination indices serve as the key factors in determining the degree to which a response is evaluated. These values contribute to a fair and accurate assessment of the response.

Stage 4. The weights θ_d and θ_f are calculated for the difficulty level and discrimination index of each task, respectively. Then, for each task, an evaluation indicators matrix is constructed, where the evaluation indicator of each task is represented as one of the five fuzzy sets. Using the fuzzy inference rules, the final evaluation level for each task is

determined. This fuzzy value is then defuzzied into a crisp score using the Center of Gravity (COG) method, resulting in the final score of each task. To represent the fuzzy values of the responses, the evaluation indicators matrix A is formed as follows:

$$A = \begin{matrix} T_1 \\ T_2 \\ \vdots \\ T_m \end{matrix} \begin{pmatrix} \overset{L}{\overbrace{a_{11}}} & \overset{LS}{\overbrace{a_{12}}} & \overset{M}{\overbrace{a_{13}}} & \overset{SH}{\overbrace{a_{14}}} & \overset{H}{\overbrace{a_{15}}} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & a_{m4} & a_{m5} \end{pmatrix} \tag{5}$$

Where:

$a_{iw} \in [0,1]$, $1 \le i \le$, $1 \le w \le 5$, indicates the degree to which the evaluation indicator of task T_i belongs to one of the five fuzzy sets. For convenience, these five fuzzy sets can be categorized into the following levels: 1 – "Low", 2 – "Slightly Low", 3 – "Medium", 4 – "Slightly High", 5 – "High".

Given the difficulty level w_d and the discrimination level w_f, the evaluation level w of the response can be determined using the fuzzy inference rules R_A provided in Table 1. The value of a_{iw} is then calculated using the following formula:

$$a_{iw} = \max_{\{(w_d,w_f)|R_A(w_d,w_f)=w\}} \left\{\theta_f d_{i,w_d} + \theta_f d_{i,w_f}\right\} \tag{6}$$

Where:

$$1 \le i \le m,\ 0 \le w \le 5\ .$$

If a task has a high level of complexity and a high discrimination index, it indicates that the task is intended for students with a high level of knowledge and provides a more accurate means of assessing their performance.

Stage 5. Calculating the weight of the response based on the importance of each task. This indicator is used to measure the influence of each task in the evaluation process. If there is a larger variation in the scores assigned to a particular task, then that task plays a more significant role in the assessment -i.e., the weight of the task increases. The response weight of each task is calculated based on the score matrix M, using the following formula:

$$c_i = \frac{1}{2} \times \left(\frac{1}{m} + \frac{\sum_{h=1}^{l} \sum_{t=1}^{l} \left| \frac{1}{n} \sum_{j=1}^{n} p_{hij} - \frac{1}{n} \sum_{j=1}^{n} p_{tij} \right|}{\sum_{i=1}^{m} \sum_{h=1}^{l} \sum_{t=}^{l} \left| \frac{1}{n} \sum_{j=1}^{n} p_{hij} - \frac{1}{n} \sum_{j=1}^{n} p_{tij} \right|} \right), \tag{7}$$

Where:

$$0 \le c_i \le 1, and\ \ 1 \le i \le m.$$

Stage 6. Each c_i value is classified into five fuzzy categories, and a weight value is calculated for each corresponding fuzzy category. As a result, the fuzzy response weight matrix C is constructed as follows:

$$C = \begin{matrix} T_1 \\ T_2 \\ \vdots \\ T_m \end{matrix} \begin{pmatrix} \overset{L}{\overbrace{c_{11}}} & \overset{SL}{\overbrace{c_{12}}} & \overset{M}{\overbrace{c_{13}}} & \overset{SH}{\overbrace{c_{14}}} & \overset{H}{\overbrace{c_{15}}} \\ c_{21} & c_{22} & c_{23} & c_{24} & c_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{m1} & c_{m2} & c_{m3} & c_{m4} & c_{m5} \end{pmatrix} \tag{8}$$

Where:

$c_{iw} \in [0,1]$ $c_{iw} \in [0,1]$ *and* $1 \le i \le m, 1 \le w \le 5$ represent the response weight value of task T_i corresponding to one of the five fuzzy sets.

Stage 7. Based on the evaluation matrix A, the fuzzy response weight matrix C, and the fuzzy inference rules, the correction value for each task is calculated. In this process, the response value a_i and the response weight c_i for each task T_i are used to compute the weights θ_a and θ_c using the following formulas:

$$\theta_a = \frac{1}{2} \times \left(\frac{1}{2} + \frac{\sum_{i=1}^{m} \sum_{k=1}^{m} |a_i - a_k|}{\sum_{i=1}^{m} \sum_{k=1}^{m} |a_i - a_k| + \sum_{i=1}^{m} \sum_{k=1}^{m} |c_i - c_k|} \right), \tag{9}$$

$$\theta_c = \frac{1}{2} \times \left(\frac{1}{2} + \frac{\sum_{i=1}^{m} \sum_{k=1}^{m} |c_i - c_k|}{\sum_{i=1}^{m} \sum_{k=1}^{m} |a_i - a_k| + \sum_{i=1}^{m} \sum_{k=1}^{m} |c_i - c_k|} \right) \tag{10}$$

It is important to note that θ_a evaluates the quality of the response, while θ_c assesses the importance of the task [14].

Stage 8. Formation of the fuzzy correction values matrix. Fuzzy correction values take into account how well the tasks align with the intended evaluation criteria and the adjustments made to improve the assigned scores. This matrix is populated with values determined based on fuzzy sets for each task and is denoted as follows:

$$E = \begin{matrix} \\ T_1 \\ T_2 \\ \vdots \\ T_m \end{matrix} \begin{pmatrix} \overset{L}{\widehat{e_{11}}} & \overset{SL}{\widehat{e_{12}}} & \overset{M}{\widehat{e_{13}}} & \overset{SH}{\widehat{e_{14}}} & \overset{H}{\widehat{e_{15}}} \\ e_{21} & e_{22} & e_{23} & e_{24} & e_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & e_{m3} & e_{m4} & e_{m5} \end{pmatrix} \tag{11}$$

The membership value $e_{iw} \in [0,1]$ indicates the degree to which the fuzzy correction value of task T_i belongs to the w-th fuzzy set. Given the response evaluation level w_a and the response weight w_c, the correction level w is determined according to the fuzzy inference rule base R_E presented in Table 1. The correction membership value e_{iw} is calculated as follows:

$$e_{iw} = \max_{\{(w_a,w_c)|R_E(w_a,w_c)=w\}} \{\theta_a d_{i,w_a} + \theta_c d_{i,w_c}\}, \ 1 \le i \le m, 1 \le w \le 5 \tag{12}$$

Where:

d_{i,w_a} – *membership degree of task* T_i *corresponding to response evaluation level* ω_a

d_{i,w_c} – membership degree of task T_i *corresponding to response weight* w_c

θ_a, θ_c – weighting coefficients

m – *total number of tasks*

For each task T_i, the correction level a_i is calculated using the Center of Gravity (COG) defuzzification method as follows:

$$e_i = \frac{0.1 \times e_{i1} + 0.3 \times e_{i2} + 0.5 \times e_{i3} + 0.7 \times e_{i4} + 0.9 \times e_{i5}}{e_{i1} + e_{i2} + e_{i3} + e_{i4} + e_{i5}}, \qquad 1 \le i \le m, 1 \le w \le 5. \tag{13}$$

The obtained value a_i represents the final crisp correction level for task T_i which integrates the membership degrees of all fuzzy correction sets into a single quantitative indicator.

Stage 9. Adjustment of evaluation indicators and computation of the final result. In this step, the initial scores for each task are updated by incorporating the corresponding fuzzy correction value, resulting in new adjusted scores. This process is carried out to improve the accuracy of the evaluation and to ensure fair outcomes [8, 12].

The adjusted score for each task T_i is calculated as follows:

$$\tilde{t}_i = t_i \times (1 + e_i). \tag{14}$$

Thereafter, the overall adjusted score vector is represented in the following form:

$$P_A = M \times \begin{pmatrix} \frac{1}{q_1} 0 \cdots 0 \\ 0 \frac{1}{q_2} \cdots 0 \\ \vdots \ \vdots \ \ddots \ \vdots \\ 0 \ \ 0 \cdots \frac{1}{q_m} \end{pmatrix} \times \left(\frac{100\tilde{s}_1}{\sum_{i=1}^{m} \tilde{s}_i}, \frac{100\tilde{s}_2}{\sum_{i=1}^{m} \tilde{s}_i}, \ldots, \frac{100\tilde{s}_m}{\sum_{i=1}^{m} \tilde{s}_i} \right)^T . \quad (15)$$

Where:

P_A – *overall adjusted score vector*
M – *evaluation matrix*
q_i – *normalization or weighting coefficient of the* $i-th$ *task*
s_i – *newly adjusted score of the* $i-th$ *task*
m – *total number of tasks*
T – *transpose operator*

In this process, the newly adjusted scores are normalized and transformed into the overall adjusted score vector, which is used as the basis for the final evaluation of each response.

4. Results

This study examined the differences between the fuzzy logic-based evaluation approach proposed in this article and the traditional assessment system. The main objective of the research was to reduce subjectivity in the evaluation of students' knowledge and to improve the consistency of the decision-making process. The fuzzy evaluation system was applied to determine task scores by taking into account multiple evaluation factors within a unified framework. In the study, scores were collected from 100 students across 5 tasks, evaluated using a [0–10] point scale.

At the initial stage, the traditional assessment scores for each student were established. These scores were assigned based on the tasks completed by the students and were evaluated using a conventional assessment system. Table 2 presents the traditional scores of 10 representative students selected from the full dataset of 100 students for illustrative comparison across 5 different tasks.

Table 2. Student scores based on the traditional assessment system

Student	Task 1	Task 2	Task 3	Task 4	Task 5	Sum
Student 1	7	8	6	9	5	35
Student 2	8	7	8	8	7	38
Student 3	6	5	7	6	5	29
Student 4	9	9	9	10	8	45
Student 5	5	6	5	7	6	29
Student 6	7	8	7	8	7	37
Student 7	8	8	8	9	8	41
Student 8	6	5	6	7	6	30
Student 9	7	7	8	9	7	38
Student 10	9	8	9	10	9	45

Table 3. Adjusted student scores obtained using the proposed fuzzy logic-based assessment model

Student	Task 1	Task 2	Task 3	Task 4	Task 5	Sum
Student 1	8.4	9.2	7.2	9.8	6.4	41.0
Student 2	8.6	8.4	8.5	9.0	7.5	41.0
Student 3	6.2	5.1	7.1	6.3	5.4	29.1
Student 4	9.5	9.5	9.8	10.0	8.8	47.6
Student 5	5.5	6.4	5.5	7.3	6.5	31.2
Student 6	7.8	8.4	7.6	8.4	7.8	39.6
Student 7	8.5	8.6	8.7	9.3	8.4	43.5
Student 8	6.3	5.4	6.5	7.1	6.2	31.5
Student 9	7.8	7.3	8.3	9.1	7.6	39.1
Student 10	9.4	8.7	9.5	10.0	9.1	46.7

Based on the fuzzy evaluation system, correction values were calculated for each task, and the adjusted scores were updated for each student. Using the fuzzy system, the final scores for each student were determined by incorporating the corresponding fuzzy correction values. Table 3 presents the final scores obtained through the fuzzy evaluation approach.

By comparing the scores presented in Tables 2 and 3, it can be observed that the fuzzy evaluation framework provides a more differentiated interpretation of student performance (Fig. 3.). The obtained results suggest that the proposed approach can reflect students' performance in a more balanced way than the traditional assessment method, particularly by taking into account task-related evaluation factors and reducing uncertainty in the assessment process.

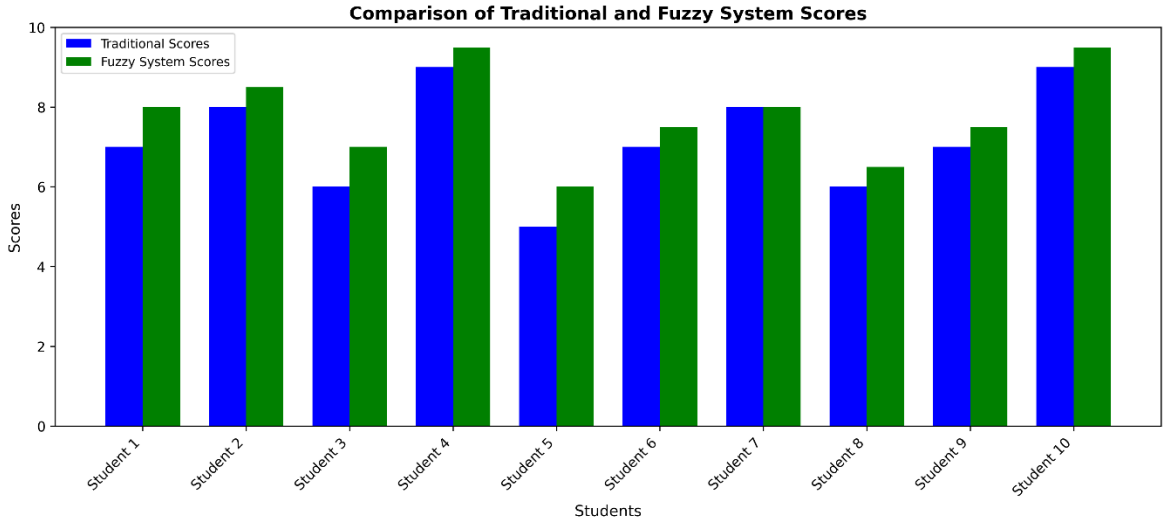


Fig 3. Comparative analysis of traditional and multi-factor fuzzy assessment results

The results also indicate that traditional assessment systems may not fully reflect the relationship between a student's actual level of knowledge and the assigned grade, especially when task complexity and academic significance are not considered. In this respect, the proposed fuzzy logic-based framework can support a more flexible and consistent evaluation process by incorporating factors such as task complexity, discrimination index, response value, and response weight. As a result, the model may contribute to a more objective and fair assessment of students' knowledge and skills.

4.1. Result Discussion

The obtained results indicate that the proposed fuzzy logic-based assessment model provides a more differentiated interpretation of student performance than the traditional scoring approach. As shown in Tables 2 and 3, the adjusted scores generated by the fuzzy model are not formed through a simple uniform increase. Instead, they are refined by considering task difficulty, discrimination index, response value, and response weight within a unified inference process.

Compared with the traditional method, the fuzzy assessment model better reflects differences among students with similar total scores. This is important because students may achieve close final marks while demonstrating different levels of performance across individual tasks. By incorporating fuzzy correction values, the proposed model reduces the influence of rigid score boundaries and provides a more balanced evaluation of learning outcomes.

The results presented in Fig. 3 also show that the fuzzy system produces smoother and more interpretable score adjustments. This suggests that the model can support instructors in making more consistent and transparent assessment decisions. However, the obtained results should be interpreted within the scope of the experimental setting, which included 100 students and 5 tasks. Further validation using larger datasets, different subjects, and real learning management system data is required to confirm the general applicability of the proposed approach.

Overall, the discussion confirms that the proposed multi-stage fuzzy model improves the flexibility and consistency of student knowledge assessment while preserving interpretability in the final decision-making process.

5. Conclusion

In this study, a multi-stage fuzzy logic-based approach for student knowledge assessment was developed and analyzed. The proposed model combines task difficulty, discrimination index, response value, and response weight within a unified evaluation framework, and also applies a correction mechanism to improve the consistency of the final results. In contrast to traditional assessment methods, which often rely mainly on direct scoring and may be affected by subjective judgment, the proposed approach allows multiple evaluation factors to be considered simultaneously within a structured decision-making process.

The results obtained in this study show that the proposed fuzzy assessment framework can provide a more balanced and consistent interpretation of student performance. By taking into account the complexity of tasks, differences in discrimination power, and the relative importance of responses, the model supports a more objective assessment process

and helps reduce uncertainty in evaluation. This is particularly important in educational practice, where students with similar total scores may demonstrate different levels of understanding across individual tasks.

From a practical point of view, the proposed model can support instructors in making more informed and consistent assessment decisions. It may also contribute to improving fairness and transparency in the educational evaluation process by reducing the dependence on rigid scoring boundaries and by incorporating several assessment indicators into one integrated framework. In this way, the model can be useful not only for current classroom assessment practices but also as a basis for the development of adaptive and intelligent educational assessment systems.

Overall, the study demonstrates that fuzzy logic can be effectively applied to student knowledge assessment when evaluation is treated as a multi-factor decision-making problem. The proposed approach has practical value for improving the quality of assessment and may serve as a useful foundation for further research on automated, adaptive, and interpretable educational evaluation models.

6. Limitations and Future Work

Although the proposed fuzzy logic-based assessment model showed promising results, this study has several limitations. First, the experimental validation was conducted using assessment data from 100 students and 5 tasks, which may limit the generalization of the results to other courses, institutions, or larger educational datasets. Second, the model was evaluated mainly by comparing traditional and fuzzy-adjusted scores, while broader statistical validation and comparison with other intelligent assessment methods were not included.

Future work will focus on testing the proposed model using larger and more diverse datasets collected from different subjects and educational levels. In addition, further research may investigate the sensitivity of membership functions, fuzzy rules, and weighting coefficients to improve the robustness of the model. Another important direction is the integration of the proposed assessment framework into learning management systems, where it can be applied for automated, adaptive, and real-time student performance evaluation.

All the Declarations and Statements

Author Contribution Statement

J. Kuvandikov – Conceptualization, methodology, model development, and manuscript preparation: Contributed to the development of the multi-stage fuzzy logic-based assessment model, participated in structuring the evaluation framework, and contributed to writing and revising the manuscript.
U. Mingboev – Formal analysis and implementation support: Assisted in the development of the evaluation procedure, supported data organization and model implementation, and contributed to the analysis of the obtained results.
M. Tojiyev – Supervision, validation, and corresponding author responsibilities: Supervised the overall research process, contributed to methodological refinement and interpretation of the results, and coordinated the preparation and submission of the manuscript.
A. Parmanov – Mathematical formalization and algorithmic support: Contributed to the mathematical description of the model, supported the formulation of the fuzzy evaluation procedure, and assisted in reviewing the technical content.
E. Hafizov – Writing, editing, and formatting: Contributed to manuscript editing, formatting, and literature organization, and assisted in improving the clarity and consistency of the paper.

Conflict of Interest Statement

The Authors declared no conflicts of interest.

Funding Declaration

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Data Availability Statement

The data used in this study consist of student assessment results analyzed within the scope of the proposed model. The data are not publicly available due to institutional and privacy considerations but may be provided by the corresponding author upon reasonable request.

Ethical Declarations

This study was based on anonymized student assessment data used only for research and methodological analysis. No personally identifiable information was disclosed in the manuscript.

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Declaration of Generative AI in Scholarly Writing

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References

[1] P. Kravets, V. Lytvyn, Y. Burov, V. Vysotska, L. Chyrun and V. Panasyuk, "Making Optimal Decisions with Learning Method Based on Fuzzy Logic," 2021 IEEE 4th International Conference on Advanced Information and Communication Technologies (AICT), Lviv, Ukraine, 2021, pp. 183–188, doi: 10.1109/AICT52120.2021.9628983.

[2] Y. Kuang, Y. Tang and T. Xie, "Objectives, Methods, and Challenges of Applying Intelligent Assessment in Education: A Systematic Review," 2024 International Symposium on Educational Technology (ISET), 2024, pp. 185–190, doi: 10.1109/ISET61814.2024.00044.

[3] L. A. Zadeh, "Fuzzy sets," Information and Control, vol. 8, no. 3, pp. 338–353, 1965, doi: 10.1016/S0019-9958(65)90241-X.

[4] T. Lin and C. S. G. Lee, "Neural-network-based fuzzy logic control and decision system," IEEE Transactions on Computers, vol. 40, no. 12, pp. 1320–1336, doi: 10.1109/12.106218.

[5] R. Imamguluyev, S. B. Hashim and I. Hajiyev, "Harnessing Uncertainty: Integrating Fuzzy Logic into Machine Learning Algorithms," 2024 4th International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 2024, pp. 510–514, doi: 10.1109/ICPCSN62568.2024.00086.

[6] E. Ferreyra, H. Hagras, M. Kern and G. Owusu, "Depicting Decision-Making: A Type-2 Fuzzy Logic Based Explainable Artificial Intelligence System for Goal-Driven Simulation in the Workforce Allocation Domain," 2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), New Orleans, LA, USA, 2019, pp. 1–6, doi: 10.1109/FUZZ-IEEE.2019.8858933.

[7] Y. Qu and O. Ogunkunle, "Enhancing the Intelligence of the Adaptive Learning Software through an AI assisted Data Analytics on Students Learning Attributes with Unequal Weight," 2021 IEEE Frontiers in Education Conference (FIE), Lincoln, NE, USA, 2021, pp. 1–6, doi: 10.1109/FIE49875.2021.9637387.

[8] G. Martinez, O. Abuomar, J. Perry, and K. Kane, "A Classroom Activity Ontology and Knowledge-Based Assessment Approach," 2022 IEEE Frontiers in Education Conference (FIE), Uppsala, Sweden, 2022, pp. 1–9, doi: 10.1109/FIE56618.2022.9962458.

[9] D. Schmidt and M. Uzulis, "Using Learning Objective-based Course Modeling for Complete Exercise Generation: From Course Material to an Aggregated Knowledge Representation," 2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE), Auckland, New Zealand, 2023, pp. 1–8, doi: 10.1109/TALE56641.2023.10398291.

[10] N.Raximov, J.Kuvandikov, D.Khasanov, "The importance of loss function in artificial intelligence", International Conference on Information Science and Communications Technologies (ICISCT 2022), DOI: 10.1109/ICISCT55600.2022.10146883

[11] Z. Wang, J. Wan, Y. Yang, C. Zeng and J. Shen, "Unified Knowledge Tracing Framework for Subjective and Objective Assessments," 2024 International Conference on Intelligent Education and Intelligent Research (IEIR), Macau, China, 2024, pp. 1–8, doi: 10.1109/IEIR62538.2024.10959908.

[12] I. Hatzilygeroudis, C. Koutsojannis, C. Papavlasopoulos and J. Prentzas, "Knowledge-Based Adaptive Assessment in a Web-Based Intelligent Educational System," Sixth IEEE International Conference on Advanced Learning Technologies (ICALT'06), Kerkrade, Netherlands, 2006, pp. 651–655, doi: 10.1109/ICALT.2006.1652526.

[13] B.Z.Parmanov, F.M.Nazarov and M.R.Tojiyev, "Development of an Algorithm for Intelligent Analysis of Data From a Microprocessor-Based Portable Spectrophotometer," 2025 International Russian Smart Industry Conference (SmartIndustryCon), Sochi, Russian Federation, 2025, pp. 664-669, doi: 10.1109/SmartIndustryCon65166.2025.10985982.

[14] N. U. Jan, S. Naqvi, and Q. Ali, "Using Fuzzy Logic for Monitoring Students Academic Performance in Higher Education," Engineering Proceedings, vol. 46, no. 1, p. 21, 2023, doi: 10.3390/engproc2023046021.

[15] J. Hu, H. Wang, and D. Ji, "Educational performance evaluation based on fuzzy evaluation model," Discover Computing, vol. 28, no. 1, 2025, doi: 10.1007/s10791-025-09854-1.

[16] A. Barlybayev, B. Razakhova, A. Sharipbay, A. Nazyrova, N. Tursynova, A. Zulkhazhav, and G. Yelibayeva, "Comparative analysis of grading models using fuzzy logic to enhance fairness and consistency in student performance evaluation," Cogent Education, vol. 12, no. 1, 2025, doi: 10.1080/2331186X.2025.2481008.

[17] H. Ergin and E. Nasibov, "Analyzing Students' Academic Performance Based on Fuzzy Inference System," Applied Sciences, vol. 15, no. 23, p. 12755, 2025, doi: 10.3390/app152312755.

[18] Raximov N.O., Dusanov X.T., Kuvandikov J.T., Daminova B.E. As a mechanism that achieves the goal of decision management IEEE International Conference on Information Science and Communications Technologies: applications, trends and opportunities (ICISCT). – 2021.
[19] M. Tomovic, C. Tomovic, V. Jovanovic, and S. Bawab, "Application of Fuzzy Logic for Evaluation of Student Performance," in INTED2025 Proceedings: 19th International Technology, Education and Development Conference, Valencia, Spain, 2025, pp. 6803–6812, doi: 10.21125/inted.2025.1751.
[20] Maruf R.Tojiyev, Sanjar S. Kenjaev, Rashid Nasimov, Oybek D.Primkulov and Gulnoza K.Ernazarova, "Quantum computing algorithm for optimizing query distribution based on multi-criteria parameters in information systems," 2025 ICFNDS, in press.
[21] J. Yang, "Fuzzy comprehensive evaluation system and decision support system for learning management of higher education online courses," Scientific Reports, 2025, doi: 10.1038/s41598-025-01782-w.
[22] É. Karl, E. Nagy and G. Molnár, "Advanced Examination Systems: Applying Fuzzy Logic and Machine Learning Methods in Education," 2025 IEEE 12th International Conference on Computational Cybernetics and Cyber-Medical Systems (ICCC), Mahe Island, Beau Vallon, Seychelles, 2025, pp. 231–236, doi: 10.1109/ICCC64928.2025.10999148.

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