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Comparative analysis of grading models using fuzzy logic to enhance fairness and consistency in student performance evaluation

Alibek Barlybayev, Bibigul Razakhova, Altynbek Sharipbay, Aizhan Nazyrova, Nazira Tursynova, Altanbek Zulkhazhav and Gaziza Yelibayeva

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ABSTRACT

The article examines the continuous assessment of student performance as a crucial element of modern educational processes for achieving learning objectives. Traditional assessment methods, such as exams and grading systems, do not always reflect the diversity of learning styles and individual characteristics of students, creating gaps in fairness and accuracy. As a solution to this issue, the study proposes a Fuzzy Logic Model (FLM), which serves as an innovative approach to assessing student performance. The study, conducted on a sample of 33 students enrolled in the 'Object-Oriented Programming in Java' course, compares the effectiveness of the FLM with traditional grading systems such as national standards, arithmetic mean, as well as institutional schemes including the U.S. Grade Point Average system and India's Central Board of Secondary Education system. The advantage of the FLM lies in its ability to model uncertainty and subjective elements of assessment, making the system more flexible and comprehensive. The results of the study show that the FLM can provide a fairer, more accurate and individualized assessment, better reflecting the complexity and multifaceted nature of student performance. The article emphasizes the importance of continuously improving assessment methods to meet modern educational demands, highlighting the relevance of using adaptive models such as fuzzy logic to enhance educational outcomes and increase the fairness of assessments.

IMPACT STATEMENT

Ensuring fairness in student grading remains a challenge, as traditional grading systems often overlook individual learning complexities. This study examine a Fuzzy Logic Model (FLM) as an adaptive and precise assessment method. By incorporating uncertainty and subjective factors, FLM provides a more nuanced evaluation of student performance. We compare FLM with conventional grading models, including national standards, arithmetic mean, and institutional systems (e.g., GPA, CBSE), using data from a Java programming course. The results indicate that FLM enhances grading fairness and consistency, reducing biases in traditional assessments. This innovative approach can improve student evaluation, ensuring a transparent, just, and personalized grading process while fostering an inclusive learning environment.

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Introduction

The assessment of student performance is a critical process in evaluating how well students meet educational objectives (Saleh & Kim, 2009). This process typically involves a variety of measures including examinations, assignments, tests, quizzes and research projects (Daud et al., 2011). To ensure fairness and transparency, it is imperative that these assessments are conducted impartially. However, assessment methods often suffer from inherent subjectivity, which may lead to discrepancies in the evaluation of student performance (Ingoley & Bakal, 2012). It is essential, therefore, that the assessment system is

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continuously scrutinized and refined to ensure its fairness, appropriateness and utility to all stakeholders. Such a system should be transparent, objective and incorporate logical reasoning, allowing for straightforward computerized implementation to objectively gauge student performance in abstract terms (Henriques et al., 2018). Moreover, the grading outcomes, which are significant indicators of a student's knowledge level, can be skewed by marginal differences. For example, the distinction between grades awarded to students with nearly identical abilities – such as an 'A' for a score of 90 versus a 'B' for a score of 89 – highlights potential inequities. Additionally, variability in teacher judgments can lead to inconsistent grading for similar efforts and achievements, underscoring the need for a more standardized approach to assessing student performance.

Traditional education systems predominantly rely on classical methods of performance assessment, where student success is typically measured by exam outcomes, categorizing results strictly as pass or fail. However, these conventional approaches often fail to accommodate the complexities of individual student learning and the inherent variability in educational achievement. To address these limitations, alternative methodologies such as fuzzy logic offer a nuanced means of assessment that can incorporate a broader range of decision-making contexts, including those found in research on techniques and artificial intelligence (Barlybayev et al., 2016; Gokmen et al., 2010; Yadav & Singh, 2011).

Fuzzy sets, introduced by Lotfi A. Zadeh in his seminal 1965 paper 'Fuzzy Sets', represent a significant advancement in the field of mathematics and logic, particularly in dealing with uncertainty and imprecision (Zadeh, 1965). Traditional set theory operates on binary membership—an element either belongs to a set or it does not. In contrast, fuzzy set theory allows for degrees of membership, enabling a more nuanced representation of concepts that are not strictly defined. A fuzzy set is characterized by a membership function that assigns each element a value between 0 and 1. This value indicates the degree to which the element belongs to the set. For example, in a fuzzy set representing 'tall people', an individual who is 6 feet tall might have a membership value of 0.8, while someone who is 5 feet tall might have a membership value of 0.2. This flexibility allows fuzzy sets to model real-world situations more accurately than classical sets. Zadeh's introduction of fuzzy sets has profoundly influenced both theoretical research and practical applications across numerous disciplines. By allowing for partial memberships, fuzzy sets provide a powerful tool for modeling complex systems where traditional binary logic falls short.

Fuzzy logic is particularly effective in managing the intrinsic uncertainties associated with subjective teacher evaluations, allowing for the modeling of student performance in more flexible, linguistic terms (Darwish, 2017). This approach not only facilitates a more comprehensive view by incorporating diverse perspectives but also reduces bias in the assessment process and encourages active student participation. Unlike binary systems that operate on absolute truths – classifying elements strictly as true or false – fuzzy logic recognizes the complexities of human cognition, which does not adhere strictly to binary reasoning. This system is inspired by human cognitive processes, which handle control challenges in a naturally imprecise manner, thus accommodating the subtleties of subjective judgment and providing a framework for the effective handling of linguistic variables and the inherent ambiguities they represent.

The utilization of fuzzy logic for student performance assessment has been a significant research topic for many years, providing a robust framework to enhance the evaluation mechanisms within educational systems. This approach is particularly advantageous in situations where educators face uncertainties in appraising students' knowledge, showcasing the potential of fuzzy logic to mitigate these challenges effectively. Historically, fuzzy logic has been applied in diverse contexts to refine educational assessments. Examples include the generation of student grades based on performances in two exams (Gokmen et al., 2010) and the evaluation of students' knowledge by integrating the outcomes of three different exams, one being practical (Petrudi et al., 2013). Further advancements have seen the development of models that assess student knowledge by considering a range of factors affecting final performance, such as the originality of students' work (Saliu, 2005) and the integration of grades and attendance records to appraise students' comprehension (Namli & Şenkal, 2018).

Empirical studies by Gokmen et al. (2010) demonstrated the tangible benefits of employing fuzzy logic in assessing university students' lab performances, underscoring the method's effectiveness as an evaluative tool. In parallel, Sripan and Suksawat (2010) advocated for the use of fuzzy scores for learning assessments, noting its flexibility and suitability for real-time assessment compared to traditional t-scores. Similarly, studies by Yıldız and Baba (2014) and Ingoley and Bakal (2012) have highlighted how fuzzy scores can enhance the transparency and fairness of student achievement assessments. These implementations exemplify how fuzzy logic can offer a more adaptable and equitable approach to educational evaluation, accommodating the inherent complexities and subjective elements present in traditional assessment methods.

Fuzzy logic has consistently demonstrated enhanced reliability over traditional assessment methods. Meenakshi and Pankaj (2015) applied this technique in 2015 using the Mamdani method to evaluate students' academic achievements, taking into account both external and internal marks as well as attendance. This innovative approach provided a comprehensive assessment framework. Additionally, Kharola et al. (2015) illustrated the flexibility of fuzzy logic by incorporating diverse attributes into the evaluation process, effectively justifying its broader application. Further utilization of fuzzy logic was seen in the work of Asopa et al. (2016), who employed a fuzzy inference system to analyze student performance, with subsequent evaluations conducted in MATLAB. This method facilitated the development of a structured approach to enhance educational systems. Yadav (2020) explored various soft computing techniques, advocating for multiple applications of fuzzy logic to accurately measure students' academic results. This discussion highlighted the potential of fuzzy logic to adapt to different educational assessment needs. Amelia et al. (2019) conducted a meta-analysis on student performance assessments using fuzzy logic, confirming its superior objectivity and transparency compared to conventional methods. Zaporozhko et al. (2020) proposed fuzzy logic as a transformative tool for online learning assessments, illustrating its growing importance in modern educational contexts. Petrudi et al. (2013) devised a model that leverages fuzzy logic to evaluate students' knowledge, integrating results from three distinct examinations, including a practical test. They contend that fuzzy logic enhances the accuracy of student performance assessments. Echoing this approach, Barlybayev et al. (2016) developed an assessment model that evaluates four key aspects of student learning: lecture evaluations, practical tasks, individual student work and a final comprehensive exam. Their findings indicate a significant and positive correlation between the outcomes derived from the fuzzy grading model and those obtained through traditional grading methods.

The primary advantage of the fuzzy grading system resides in its reliance on inference rules rather than simple arithmetic means of exam scores. This system is capable of integrating assessments on varied grading scales, thereby eliminating the necessity for standardization across different testing formats. The research collectively suggests that adopting fuzzy logic in student assessment protocols allows for a more detailed and nuanced understanding of individual performance, ultimately leading to more effective evaluations of students' learning trajectories. The paper by Voskoglou (2013) explores the application of fuzzy logic in assessing students' knowledge and skills. Traditional assessment methods often rely on binary outcomes – right or wrong answers. However, fuzzy logic introduces a more nuanced approach by allowing for degrees of truth between completely true and completely false. Voskoglou's study highlights the benefits of using fuzzy logic in educational assessment. By incorporating fuzzy sets, linguistic variables and fuzzy rules, educators can create assessment models that better capture the complexity of students' understanding. This approach enables a more holistic evaluation of students' knowledge and skills, taking into account uncertainties and ambiguities. Ivanova and Zlatanov (2019) paper underscores the importance of exploring alternative approaches to grading that can address issues of bias and inconsistency. The adoption of fuzzy functions represents a promising avenue for promoting fairer evaluation practices in education. The results of the study demonstrate that the use of fuzzy functions led to a more equitable distribution of grades among students. By incorporating fuzzy logic into the grading system, the researchers were able to account for uncertainties and variations in student performance more effectively. Such studies underscore the potential of fuzzy logic to substantially refine educational assessment practices.

The study Arora and Saini (2013) conducted by Arora and Saini focused on the development and application of a Fuzzy Probabilistic Neural Network (FPNN) for predicting students' academic performance. The primary application of the FPNN developed by Arora and Saini was in predicting students' academic performance based on various input factors such as previous grades, attendance records, study habits and other relevant parameters. By training the FPNN on historical data containing these input variables along with corresponding academic outcomes, the model can learn to make accurate predictions about future student performance. The study conducted by Daneshvar et al. (2021) aimed to develop a model for evaluating the performance of teachers in an electronic education system using an Adaptive Neuro Fuzzy Inference System (ANFIS). The study found that the ANFIS-based model was successful in assessing teacher performance within an electronic education system. By incorporating various factors and parameters into the evaluation process, the model was able to provide valuable insights into the effectiveness and efficiency of teachers in this setting. The findings highlighted the potential of using advanced computational techniques like ANFIS to enhance performance evaluation processes in educational systems. The research undertaken by Jafarkhani (2017) explores the integration of fuzzy systems into the evaluation of practical courses and the development of educational multimedia. Fuzzy logic, renowned for its capacity to manage uncertainty and imprecision – attributes prevalent in real-world situations – has become increasingly popular in educational contexts. The incorporation of fuzzy systems within assessment processes enables educators to devise evaluation methods that are both flexible and adaptive (Mehdi & Nachouki, 2023). These methods more accurately represent the true performance of students, accommodating the inherent variability and complexity of educational performance metrics. In the study conducted by Latah (2016), the author proposed ANFIS approach combined with genetic feature selection to predict students' academic performance in a distance education environment. The research aimed to enhance the accuracy of predicting students' academic outcomes by utilizing a hybrid model that integrates ANFIS and genetic algorithms for feature selection. The study by Chrysafiadi and Virvou (2012) focuses on evaluating the integration of fuzzy logic into the student model of a web-based learning environment. The researchers aimed to improve the accuracy and effectiveness of student modeling by incorporating fuzzy logic techniques. By utilizing fuzzy logic, the system can better interpret vague or ambiguous data related to student performance and adjust its responses accordingly. The study by Annabestani et al. (2020) introduces a fuzzy descriptive evaluation system aimed at providing a real, complete and fair evaluation of students. This system utilizes soft computing techniques to address the complexities and uncertainties involved in student evaluation processes. By incorporating fuzzy logic, the system can handle imprecise and vague information commonly encountered in educational assessments. The investigation led by Doz et al. (2022b) centers on the synthesis of students' academic grades and their performance on the National Assessment of Knowledge through the application of fuzzy logic. Fuzzy logic, a mathematical methodology, is characterized by its ability to facilitate approximate rather than precise and exact reasoning. This approach is particularly adept at handling the inherent uncertainties and variabilities in educational assessment. By amalgamating individual academic grades with standardized national assessment results, the researchers endeavor to furnish a holistic appraisal of students' knowledge and competencies, thereby yielding a more nuanced understanding of educational outcomes.

The paper by Doz et al. (2022a) explores the application of fuzzy logic in evaluating students' mathematical knowledge. The authors argue that traditional assessment methods often fail to capture the nuances of student understanding, particularly in subjects like mathematics where conceptual grasp can vary significantly among learners. The authors implemented a fuzzy logic system to assess mathematical knowledge by defining linguistic variables that represent different levels of understanding (eg 'low', 'medium', 'high'). They collected data from students through various mathematical tasks and used this data to create fuzzy sets. The fuzzy inference system then evaluated these sets to provide a more nuanced assessment of each student's performance. The findings indicated that using fuzzy logic provided a more comprehensive view of student understanding compared to traditional grading systems. Students who might have been classified as struggling under conventional assessments were shown to possess varying degrees of knowledge when assessed through the fuzzy logic framework.

Glushkova et al. (2024) offers significant insights into improving proficiency evaluation through innovative assessment strategies that leverage fuzzy logic within online environments. This approach not only enhances accuracy in measuring student understanding but also promotes equitable educational practices. The authors develop a hybrid model that combines traditional testing with fuzzy logic assessments. This model utilizes online practice tests where students' responses are evaluated not just on correctness but also on their reasoning processes and partial understandings. The paper discusses how this hybrid approach can be implemented in online educational platforms, enhancing the adaptability of assessments to individual learner needs. By using algorithms based on fuzzy logic, the system can provide more personalized feedback and support. One of the core aims of this research is to promote equity in educational assessments. By recognizing diverse learning paths and providing tailored evaluations, the proposed method seeks to ensure that all students have an equal opportunity to demonstrate their knowledge and skills. Preliminary results from implementing this approach indicate improved student engagement and satisfaction with assessments. The authors suggest that further research is needed to refine these methodologies and explore their long-term impacts on learning outcomes.

The paper by Doz, Cotič and Felda explores the application of random forest regression in predicting students' academic achievements and fuzzy grades. This research is situated within the broader context of educational data mining and machine learning, where predictive analytics are increasingly utilized to enhance educational outcomes. Fuzzy grading systems introduce a level of ambiguity into traditional grading methods by allowing for a range of scores rather than fixed grades. This approach acknowledges that student performance may not fit neatly into categorical boundaries. The integration of fuzzy logic with random forest regression enables the model to predict not just discrete grades but also a spectrum of potential outcomes based on input variables.

The paper by Doz et al. (2023) investigates how various demographic factors influence fuzzy grading systems through a hierarchical linear regression analysis. The results indicated significant relationships between these demographic factors and students' perceptions of fuzzy grading. Students from higher socioeconomic backgrounds tended to view fuzzy grading more positively than those from lower socioeconomic backgrounds. Older students were generally more accepting of fuzzy grades compared to younger peers who might prefer traditional methods. Gender differences emerged, with female students showing a greater inclination toward embracing innovative assessment methods. These findings suggest that demographic characteristics play a crucial role in how students perceive and respond to alternative grading systems like fuzzy grading.

In the paper by Algshat (2024), fuzzy logic is applied to evaluate students' academic progress through various metrics such as test scores, participation and assignment completion rates. The approach involves defining fuzzy sets for different performance levels (eg low, medium, high) and using membership functions to quantify how well a student's performance aligns with these categories. For instance, a student's score might be classified as 'medium' if it falls within a certain range but does not fit neatly into 'low' or 'high'. By moving beyond rigid grading systems, educators can foster an environment that recognizes individual learning trajectories and supports diverse student needs.

The primary goal of this research is to systematically investigate the effectiveness of different grading models by comparing their assessments of student performance across various criteria, utilizing a cohort of 33 students enrolled in an 'Object-oriented Programming in Java' course. This study aims to evaluate the accuracy, consistency and fairness of the grading outcomes produced by diverse assessment models including a traditional national standard, arithmetic mean calculations, specific institutional schemes and international grading standards such as the United States Grade Point Average (GPA) and Indian Central Board of Secondary Education (CBSE) systems. Additionally, the research explores the incorporation of a novel Fuzzy Logic Model (FLM) to determine its alignment with conventional assessment methods and its potential to enhance evaluative accuracy and adaptability in educational settings. Through this comparative analysis, the research seeks to provide insights that could influence educational assessment practices, enhance understanding of grading model efficacies and support the development of more equitable and reflective educational evaluation systems.

Materials and methods

Method for assessing students' knowledge at universities in Kazakhstan

Types of estimates and their designation: Lecture evaluation – Lec; Practical evaluation – Pra; Laboratory evaluation – Lab; Studio evaluation – Stu; Seminar evaluation – Sem; Current control – CC; Medium control – MC; Rating – Rat; Admission Rating– RA; Evaluation of the course work – Cou; Evaluation of project work – Pro; Summarizing the work rate – IP; Self work of learner – SWL; Student's self work – SWS; Self work of the student with the teacher – SWST; Self work of masters – SWM; Self work of the master with the teacher – SWMT; Self work of doctoral student – SWD; Self work of doctoral student with the teacher

Table 1. Weight fractions of each lesson's type.

Lesson's type	Weight						
Lecture	0.2	0.2	0.2	0.2	–	0.7	0.2
Practical lessons	0.5	0.2	–	–	0.7	–	0.2
Laboratory	–	0.3	0.5	–	–	–	–
Studio sessions	–	–	–	0.5	–	–	0.3
Student's self work	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Total	1	1	1	1	1	1	1

– SWDT; Exam evaluation – E; Final grade – FG; Automata evaluation – Aut; a/np – assessment is not provided; n/a – student did not attend the session.

Table 1 appears to provide the weighted share by type of occupation, which could be used to calculate an Admission Rating (RA) for educational purposes. It breaks down the type of lessons into several categories and assigns different weight fractions to each, presumably based on their importance or time spent on them in a curriculum (Issakova et al., 2021).

Table 1 structured to assign specific weightings to different types of educational sessions in a curriculum, with the purpose of calculating RA for educational institutions. The columns show the weighting factor of a particular lesson type. Each category sums to a total weight of 1.0 for each column, maintaining a normalized scale for comparison and calculation.

To calculate an Admission Rating (RA) using this table, it is need to multiply the weights by the respective grades or assessment scores in each category of lessons, sum these products and normalize them, to get a composite score that reflects the weighted importance of each type of lesson.

The assessment of academic performance among students at universities in Kazakhstan is conducted through a score-rating system. This method entails calculating the final semester grade for each subject by aggregating the rating points accrued from all evaluative activities within the discipline throughout the semester, in addition to the final examination. The composition of the final grade is weighted, with 60% attributed to continuous and mid-term assessments and the remaining 40% derived from the final examination grade.

Within the framework of the evaluation system, each form of assessment is assigned a maximum attainable score of 100 marks. This encompasses all varieties of ongoing and mid-term evaluations as detailed within the academic curriculum of the discipline, encompassing both the teaching and methodological complex and the syllabus.

The computation of the Final Grade (FG) adheres to the formula:

$$\mathrm{FG} = \mathrm{RA} \times 0.6 + \mathrm{E} \times 0.4 \tag{1}$$

Here, RA represents the Admission Rating, which is a prerequisite for the examination; E denotes the score obtained in the examination phase.

The Admission Rating (RA) is determined by calculating the arithmetic mean of the scores achieved in each form of assessment during the initial and latter halves of the semester. Eligibility to partake in the examination is contingent upon achieving a minimum Admission Rating of 50 marks, with the maximum possible Admission Rating being 100 marks.

Assignment of the Final Grade is contingent upon successful completion of the examination, adhering to a specified grading scale. This scale correlates the quantitative marks obtained with their corresponding qualitative grades, ensuring a standardized assessment of academic achievement. The assignment of the final grade is contingent upon the successful completion of the examination, in alignment with the specified grading scale delineated in the subsequent Table 2.

Table 2 is structured to provide comprehensive comparative data to evaluate student performance across various grading standards utilized globally. Grade based on letter system column lists grades from 'A' to 'F', including mid-range modifiers (eg A−, B+) which add granularity to the grading system, providing a finer scale of academic evaluation. Each letter grade is associated with a numerical value on a scale from 0 to 4.0. This scale facilitates quantitative assessment and comparison of grades, where 'A' is the highest (4.0) and 'F' is the lowest (0). Grade in % column specifies the percentage range corresponding to each grade, extending from 0–24% for an 'F' to 95–100% for an 'A'. This percentage range offers a direct link between numerical scores and their respective letter grades, indicating the level of

Table 2. Classification of grades compared to European Credit Transfer and Accumulation System (ECTS).

Grade based on letter system	Digital equivalent of grades	Grade in %	Grade in the traditional system	Grade based on ECTS
A	4.0	95–100	Very good	A
A−	3.67	90–94		
B+	3.33	85–89	Good	B
B	3.0	80–84		C
B−	2.67	75–79		
C+	2.33	70–74	Satisfactory	
C	2.0	65–69		D
C−	1.67	60–64		
D+	1.33	55–59		
D	1.0	50–54		E
FX	0.5	25–49	Fail	FX, F
F	0	0–24		

Table 3. Input estimates for example.

		Week									
Lesson's type	Weight	1	2	3	4	5	6	7	CC	MC	Rat1
Lecture	0.2	a/np	n/a	n/a	80	80	100	a/np	52	64	70.12
Laboratory	0.5	a/np	a/np	90	90	a/np	90	a/np	90		
Student's self work	0.3	a/np	a/np	70	70	a/np	75	a/np	71.67		
Total	1								76.23		

mastery achieved. Grades in the traditional system column categorize grades into descriptive terms such as 'Very good', 'Good', 'Satisfactory' and 'Fail'. These descriptors provide a qualitative assessment of the grade, which is commonly used in traditional educational systems. Grade based on ECTS column aligns the letter grades with the ECTS grades, which are standard across European educational institutions, facilitating student mobility and credit transfer. The ECTS grades range from 'A' to 'F', with 'FX' indicating a failing grade that still provides an opportunity to pass upon re-examination.

Current control (CC) is established by the weighted average of the arithmetic means for each category of educational activity. Tables 3 and 4 outline the necessary data to compute academic achievement.

Current control on lectures, laboratory, Student's self work is calculated by the arithmetic mean:

$$\mathrm{CC} = 52 * 0,2 + 90 * 0,5 + 71.67 * 0,3 = 76.23 \tag{2}$$

Rating Rat1 (Rat2) is determined in accordance with the monitoring points (CC) and the boundary control (MC):

$$Rat1(Rat2) = (CC + MC)/2 = (76.23 + 64)/2 = 70.12 \tag{3}$$

Rating tolerance for the discipline:

$$RA = (Rat1 + Rat2)/2 = (70.12 + 82.52)/2 = 76 \tag{4}$$

The final grade for the discipline is calculated as follows:

$$(\mathrm{E} = 74): \quad \mathrm{FG} = \mathrm{RA} * 0.6 + \mathrm{E} * 0.4 = 76 * 0.6 + 74 * 0.4 = 45.6 + 29.6 = 75.2 \tag{5}$$

Method for assessing students' knowledge at universities in Kazakhstan

All student performance input data are given in Table 5. And also applies to the input data and Exam evaluation. The primary input for this method encompasses the students' performance scores from various academic activities: lectures, laboratory sessions and student-directed study periods, as well as the results from examinations. The examination score is designated as E, with a value of 74. To compute the arithmetic mean, the sum of all performance evaluations across the specified categories is aggregated and subsequently divided by the total count of the data points, thus deriving the mean value.

Table 5 provides a detailed account of the input evaluations, structured weekly, across three pedagogical formats: lectures, laboratory work and self-directed study. The table encapsulates data for a span

Table 4. Input estimates example.

		Week										
Lesson's type	Weight	8	9	10	11	12	13	14	15	CC	MC	Rat2
Lecture	0.2	90	a/np	80	a/np	90	90	90	a/np	88	93	82.52
Laboratory	0.5	n/a	50	75	70	70	75	90	75	63.12		
Student's self work	0.3	50	90	75	a/np	90	a/np	a/np	a/np	76.25		
Total	1									72.04		

Table 5. Input estimates for arithmetic mean method.

Lesson's type / week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Lecture	a/np	n/a	n/a	80	80	100	a/np	90	a/np	80	a/np	90	90	90	a/np
Laboratory	a/np	a/np	90	90	a/np	90	a/np	n/a	50	75	70	70	75	90	75
Student's self work	a/np	a/np	70	70	a/np	75	a/np	50	90	75	a/np	90	a/np	a/np	a/np

Table 6. Set of classifications for the final grade.

Letter grade	Numerical value
A*	84
A	74
B	64
C	54
D	44
F	0

of 15 weeks. For the purpose of this method, such instances are omitted from the calculation. The Final Grade, serving as an output measure for the academic standing, is calculated as follows:

$$FG = \text{Mean}(Lec + Lab + Pra + SWS + E) \tag{5}$$

$$\begin{aligned} FG = {} & ((80 + 80 + 100 + 90 + 80 + 90 + 90 + 90) + (90 + 90 + 90 + 50 + 75 + 70 + 70 + 75 + 90 + 75) \\ & + (70 + 70 + 75 + 50 + 90 + 75 + 90) + 74)/29 = 71.35 \end{aligned} \tag{6}$$

The quotient derived from this computation, 71.35, quantitatively represents the Final Grade. This figure reflects the collective academic performance of a student, amalgamating both continuous assessment and final examination outcomes. The methodology thus provides a comprehensive gauge of a student's knowledge acquisition through a standardized evaluative lens.

Method for assessing students' knowledge in the university of Liverpool Grading Scheme for Masters programs

The University of Liverpool, like many institutions, has a specific grading scheme for its Masters programs to assess and classify the academic performance of its students. In general, the grading for Masters programs in the UK, including the University of Liverpool, follows a particular set of classifications for the final grade. Table 6 shows the grading set.

These classifications ensure that students' work is assessed and rewarded appropriately, reflecting their level of understanding and skills in their field of study. Each component of the program (such as coursework, exams and dissertations) is usually marked on a scale of 0–100, and the final classification is based on the weighted average of these marks.

Table 7 presents a methodology for calculating the end-of-module grade for a student excelling in the first module of their program, employing a translation of input data to numeric values as per the University of Liverpool's grading system, which employs a scale of 0 to 84 across six discrete categories. This conversion aims to align with their specific scoring criteria. Following this, Table 8 offers the translated output data, showcasing the application of these numeric values within the university's grading framework, thus illustrating the assessment process in a quantified manner.

In the context of the University of Liverpool's grading system, a score of 76.6605 is classified as grade A. This grade corresponds to a performance that, within Kazakhstan grading framework, would be

Table 7. Input estimates for Liverpool Grading Scheme.

Lesson's type / week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Lecture	a/np	n/a	n/a	A	A	A*	a/np	A*	a/np	A	a/np	A*	A*	A*	a/np
Laboratory	a/np	a/np	A*	A*	a/np	A*	a/np	n/a	D	A	B	B	A	A*	A
Student's self work	a/np	a/np	B	B	a/np	A	a/np	D	A*	A	a/np	A*	a/np	a/np	a/np
Lecture	a/np	n/a	n/a	74	74	84	a/np	84	a/np	74	a/np	84	84	84	a/np
Laboratory	a/np	a/np	84	84	a/np	84	a/np	n/a	44	74	64	64	74	84	74
Student's self work	a/np	a/np	64	64	a/np	74	a/np	44	84	74	a/np	84	a/np	a/np	a/np

Table 8. Output estimates for Liverpool Grading Scheme.

Lesson's type	Average mark	Weight	Component contributions to final module assessment
Lecture	80.25	50%	40.125
Laboratory	73	25%	18.25
Student's self work	69.71	5%	3.4855
Exam evaluation	74	20%	14.8
Total		100%	76.6605

Table 9. Grading system used by different colleges in the United States.

Letter grade	Percentage	GPA
A+	97–100%	4.0
A	93–96%	3.9
A–	90–92%	3.7
B+	87–89%	3.3
B	83–86%	3.0
B–	80–82%	2.7
C+	77–79%	2.3
C	73–76%	2.0
C–	70–72%	1.7
D+	67–69%	1.3
D	63–66%	1.0
D–	60–62%	0.7
F	0–59%	0.0

evaluated within the 90–100 points range out of a possible 100, indicating a high level of academic achievement.

Method for assessing students' knowledge in the United States by grade point average

In the academic landscape of the United States, the grading system predominantly adopts a scale comprising five to seven letter grades, encompassing A+, A, A–, B+, B, B–, C+, C, C–, D+, D, D – and F, sequentially from the highest to the lowest achievable grades. Exceptionally, an A + denotes superior academic performance, whereas F signifies failure to meet the minimum academic requirements. Additionally, certain educational institutions and disciplines may utilize numerical grading schemes. The conversion from numerical scores to letter grades exhibits variability, contingent upon the specific grading policies of an institution, the academic discipline in question and the level of study (Rubright et al., 2019). Table 9 delineates the grading systems implemented by four distinct collegiate institutions within the United States. The quantitative analysis delineating the calculation of the final GPA is predicated on the amalgamated scores derived from lectures, laboratory sessions, student's self work and an examination score, as depicted in Tables 3 and 4. This exposition will expound upon the methodology employed to convert raw scores into GPA values, followed by the computation of the aggregate GPA.

Lecture performance evaluation in corresponding GPA values: 3.0, 3.0, 4.0, 4.0, 3.0, 4.0, 4.0, 4.0.

Laboratory performance evaluation in corresponding GPA values: 4.0, 4.0, 0.0, 2.0, 2.0, 2.0, 2.0, 4.0, 2.0.

Student's self work performance evaluation in corresponding GPA values: 2.0, 2.0, 2.0, 0.0, 4.0, 2.0, 4.0.

Examination performance evaluation in corresponding GPA values: 2.0.

The final GPA is determined by aggregating the GPA values derived from lectures, laboratory sessions, student's self work and the examination. This cumulative sum is then divided by the total count of scores converted to GPA values, facilitating the computation of the mean GPA. Employing this

Table 10. Grading system used in the India.

Letter grade	Percentage
A1	90–100%
A2	80–90%
B1	70–80%
B2	60–70%
C1	50–60%
C2	40–50%
D	33–40%
E/F(failed)	0–32%

Table 11. Grading system used in the China.

Letter grade	Percentage
A+	95–100%
A	90–94%
A−	85–89%
B+	82–84%
B	78–81%
B−	75–77%
C+	72–74%
C	68–71%
C−	65–67%
D (pass)	60–64%
F (failure)	0–59%

methodology for the provided scores yields a final GPA of approximately 2.76, encapsulating the student's overall academic performance across diverse evaluative components. This grade aligns with an academic performance that, under the Kazakhstan grading schema, is quantitatively assessed within the interval of 80 to 82 points on a scale extending to a maximum of 100 points.

Method for assessing students' knowledge by Indian Central Board of Secondary Education

In Indian CBSE grades are given in percentages, with a 33% minimum passing mark. Distinctions are awarded to students scoring above 75%, reflecting a high standard of excellence (Brown et al., 2015). The CBSE employs the ensuing grading system, that shown in Table 10.

Utilizing the scores provided for lectures, laboratory sessions, student's self-work and the examination score, as depicted in Tables 3 and 4, the calculated average score is approximately 79.16. According to the grading system of the Indian CBSE, this translates to a final grade of 'B1', indicating a high level of performance.

Method for assessing students' knowledge in the China by grade point average

In Chinese higher education, the academic grading system can exhibit significant variations between different universities and colleges, but a few general principles apply widely across the country. The system combines numerical scores, grade points and sometimes letter grades to assess student performance (Wang & Chui, 2017). The prevailing grading system employed across the majority of Chinese tertiary education institutions, as well as secondary education establishments, is stratified into distinct categories. These classifications are systematically delineated in Table 11.

We calculated the final grade using the provided data, as depicted in Tables 3 and 4, within the context of the Chinese academic grading system. Without explicit weightings, a common approach involve averaging the grades from each category and then calculating the overall average considering the examination score. Then we assume the following weightings, which might vary in actual applications: Lecture – 30%; Laboratory – 30%; Student's self-work – 10%; Examination – 30%; Lecture average – 87.5; Laboratory average – 77.5; Student's self-work average – 74.3.

Taking these averages into account alongside the examination score of 74 and applying the specified weightings (30% for lectures, 30% for laboratory work, 10% for self-study and 30% for the examination), the final grade calculates to approximately 79.1. This final grade is considered a good performance, correlating to a 'B' or 'Good' category if translated into a letter grade or descriptive term.

Method for assessing students' knowledge by fuzzy logic

Creating a fuzzy inference system (FIS) student (Barlybayev et al., 2016) for assessing student knowledge at Kazakhstan universities requires defining the fuzzy sets, linguistic variables and inference rules that model the nuances of academic performance evaluation. Before building a fuzzy machine, we need to calculate Admission Rating:

$$RA = \mathrm{Mean}(\mathrm{Lec}) * 0.2 + \mathrm{Mean}(\mathrm{Lab/Pra}) * 0.5 + \mathrm{Mean}(\mathrm{SWS}) * 0.3 \tag{7}$$

$$\begin{aligned} RA = {} & (80 + 80 + 100 + 90 + 80 + 90 + 90 + 90)/10 * 0.2 \\ & + (90 + 90 + 90 + 50 + 75 + 70 + 70 + 75 + 90 + 75)/11 * 0.5 \\ & + (70 + 70 + 75 + 50 + 90 + 75 + 90)/7 * 0.3 \\ = {} & 70 * 0.2 + 70.45 * 0.5 + 74.28 * 0.3 = 14 + 35,225 + 22,284 = 71,509 \end{aligned} \tag{8}$$

Fuzzy Sets and Linguistic Variables:

- Admission Rating (RA): This is a crucial input variable reflecting continuous assessment performance. It ranges from 0 to 100, with specific linguistic terms such as Low (0–49), Medium (50–74), High (75–100).
- Examination Score (E): Another input variable representing the exam performance, also ranging from 0 to 100, categorized similarly to RA with linguistic terms Low (0–49), Medium (50–74), High (75–100).
- Final Grade (FG): The output variable that estimates the final academic standing of a student, can be represented with terms like Fail (0–49), Satisfactory (50–69), Good (70–84), Very Good (85–100).

The fuzzy rules will define the relationship between the input variables (RA and E) and the output variable (FG). Fuzzy Rules:

- If RA is Low and E is Low, then FG is Fail.
- If RA is Medium and E is Low, then FG is Fail.
- If RA is High and E is Low, then FG is Satisfactory.
- If RA is Low and E is Medium, then FG is Good.
- If RA is Medium and E is Medium, then FG is Good.
- If RA is High and E is Medium, then FG is Very Good.
- If RA is Low and E is High, then FG is Good.
- If RA is Medium and E is High, then FG is Very Good.
- If RA is High and E is High, then FG is Very Good.

The result of calculations Final Grade = 77 is shown in Figure 1. The surface between inputs and output variables described in Figure 2.

Figure 1 displays the membership functions for the input and output variables. Here, we have two input variables—Admission Rating (RA) and Examination Score (E)—and one output variable, the Final Grade (FG). In the provided image, 'input1' corresponds to RA with a value of 0.71509 and 'input2' corresponds to E with a value of 0.74, indicating that both input values fall into the 'Medium' category based on the linguistic terms given. According to the fuzzy rules described:

If RA is medium and E is medium, then FG is good

The corresponding output value for 'output1' which is FG, is shown as 0.77. This suggests that the FIS has processed the input values through the defined rules and concluded that the Final Grade is 'Good' based on the membership functions and inference rules. This output aligns with the specified result of the calculations where the Final Grade is 77, fitting within the 'Good' range (70–84) as per the provided

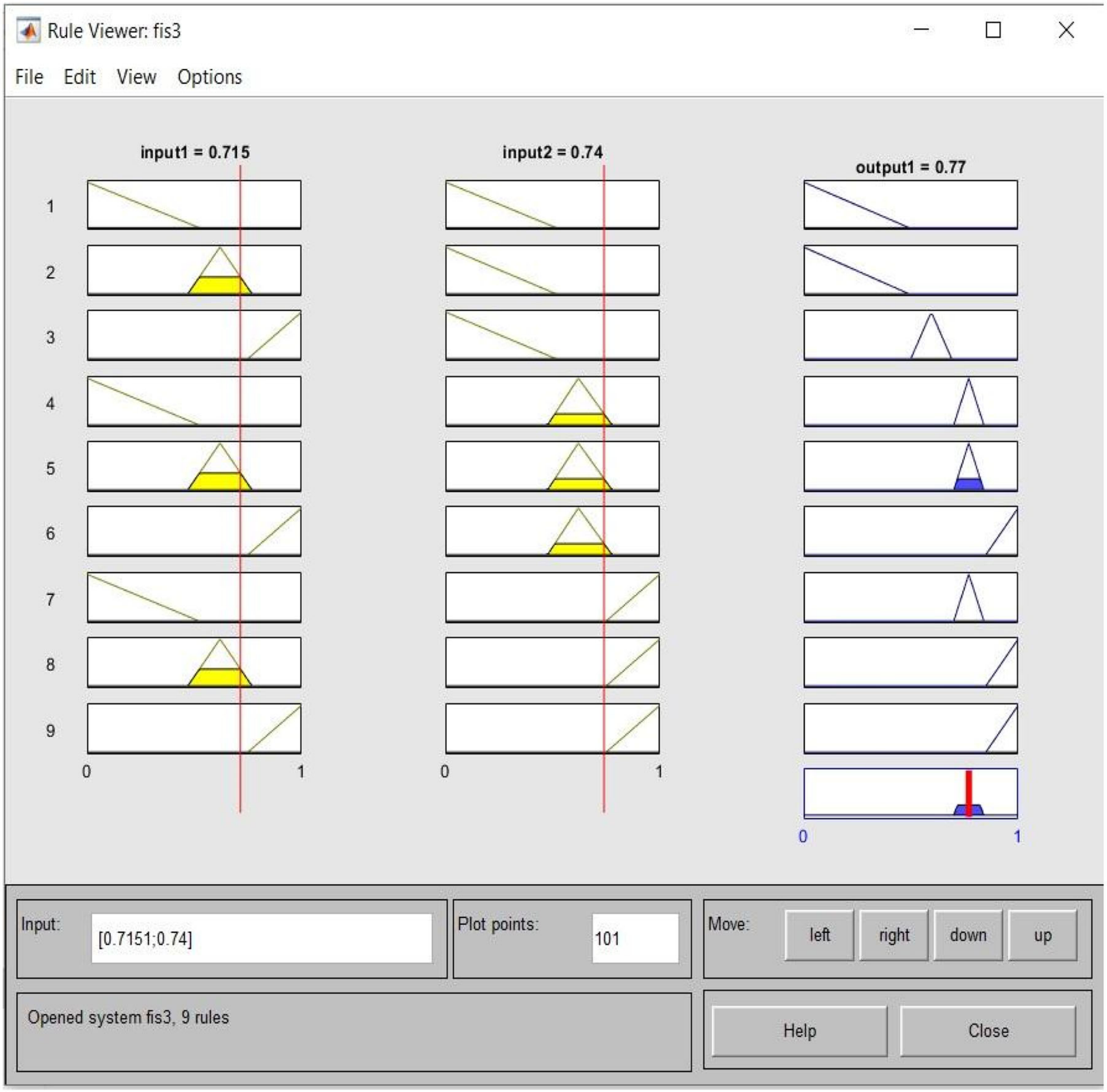

Figure 1. Calculation of final grade.

linguistic variables. The Rule Viewer visualizes how the input values are assessed against each fuzzy rule and the degree to which they satisfy the conditions of each rule, resulting in the defuzzified output which is the Final Grade in this context.

Figure 2 appears to be a screenshot from a fuzzy logic software tool, showing a Surface Viewer of a Fuzzy Inference System. This viewer is used to represent the relationship between the input and output variables in a three-dimensional space, which is essential for understanding the dynamics of the fuzzy logic system used to assess student knowledge at Kazakhstan universities. In the context of assessing student knowledge with fuzzy logic, the Surface Viewer in Figure 2 display the relationship between the two input variables—Admission Rating (RA) and Examination Score (E)—and the output variable, which is the Final Grade (FG). The three axes of the graph represent the input variables and the output variable:

- The X-axis represents ‘input1’, which is the Admission Rating (RA).
- The Y-axis represents ‘input2’, which is the Examination Score (E).
- The Z-axis represents ‘output1’, which is the Final Grade (FG).

The surface itself is color-coded and shaped according to the fuzzy rules applied in the system. It visually demonstrates how different combinations of Admission Rating and Examination Score translate

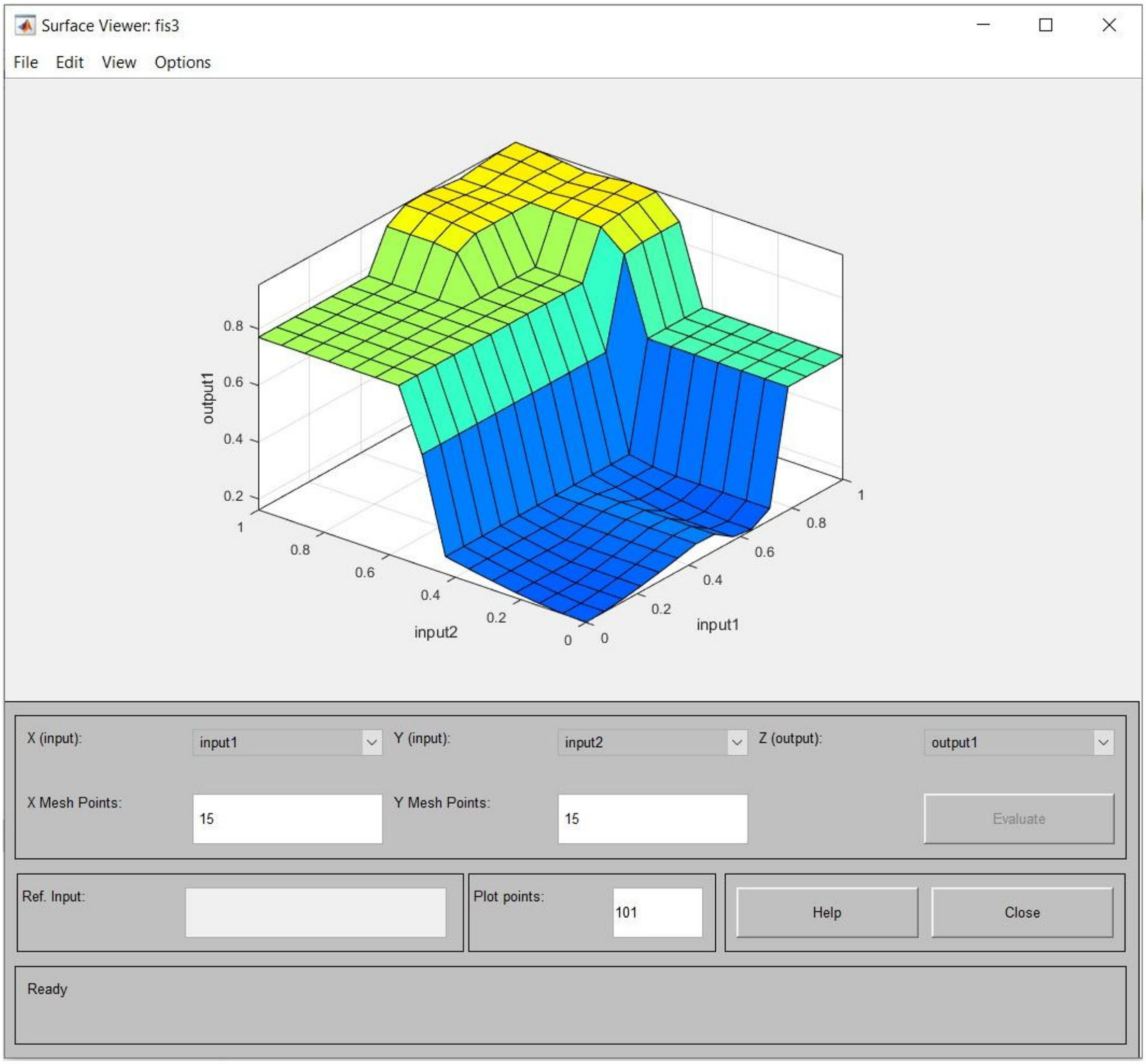

Figure 2. Surface between inputs and output variables.

into a Final Grade through the fuzzy inference process. For example, areas where the surface is higher correspond to higher Final Grades.

The provided rules guide how this surface is shaped. For instance, when both RA and E are high, the surface will rise toward the 'Very Good' range on the FG axis, according to the rules such as:

$$\textit{If RA is High and E is High, then FG is Very Good} \tag{9}$$

In contrast, when both input values are low, the surface would dip toward the lower end of the FG axis, in alignment with the rule:

$$\textit{If RA is Low and E is Low, then FG is Fail.} \tag{10}$$

Figure 2 is a visual representation of the FLM that shows how input assessments are translated into a final grading outcome based on the defined fuzzy sets, linguistic variables and inference rules. The specific surface shape is the result of the combined effect of all these rules and helps in interpreting the system's logic in a more intuitive way.

Results

For the experimental study, a cohort of 33 students was selected, all of whom were enrolled in the course titled 'Object-oriented Programming in Java'. The study sample comprised 33 students enrolled in 2 course in Kazakhstan, with a gender distribution of 9 females and 24 males. Data were extracted from an electronic journal system. The analysis of the dataset was conducted using MATLAB software. In accordance with ethical standards for research involving human subjects, all personal identifiers were removed from the dataset to ensure anonymity. Consequently, the requirement for ethical committee approval was circumvented. Prior to data collection, all participants were informed that their academic grades would be utilized for research purposes and their consent was obtained. This procedural approach aligns with ethical guidelines for educational research, ensuring transparency and confidentiality. The assessments for this course were divided into three categories: Lecture, Laboratory and Student's self work. All grades were systematically recorded in the tutor's electronic logbook. Specifically, the grades awarded for the lecture component of the 'Object-oriented Programming in Java' course are summarized in Table 12. This table provides a comprehensive overview of both the continuous assessment scores during the semester and the final exam results.

Furthermore, the performance outcomes from the laboratory sessions associated with the same course are detailed in Table 13. This includes scores from lab exercises and project work, emphasizing the application of theoretical concepts learned during lectures.

Table 14 presents the grades assigned for independent tasks completed as part of the 'Object-oriented Programming in Java' course. These tasks were designed to encourage self-directed learning and the development of problem-solving skills outside of the structured classroom and lab environments.

Table 15 provides a comprehensive overview of assessment results for 33 students across different grading models. The grading models compared include: National standard model used in Kazakhstan; Arithmetic Mean model calculates the average of all grades received across different evaluation criteria; A specific grading scheme, used by an educational institution in Liverpool; Translating model GPA into percentage values as used in the United States educational system; Grading model used by the Central Board of Secondary Education in India; GPA system used in Chinese educational institutions; Student's performance evaluation model by fuzzy logic.

Table 15 demonstrates the importance of understanding the context and criteria of different grading systems when assessing academic performance. The variability seen across models highlights the challenge in creating a universally applicable grading system that fairly and accurately reflects student performance. This table suggests that while 'Proposed Fuzzy Logic Model' may align to a degree with established assessment schemes, additional refinement and validation might be required to ensure its effectiveness and acceptance in broader educational settings. The data shows significant variability in how each model scores the same student. For example, Student 18 scored a 51 in the Kazakhstan model and only 30.6 in the Liverpool Grading Scheme, but reached as high as 59 in the U.S. GPA Percentage model. This variance illustrates how different educational standards and criteria can significantly influence student assessments. Students such as 9, 12, 27 and 31 consistently show high performance across all models, indicating a strong overall academic ability. Conversely, students like 18 and 19 have consistently lower scores, which might indicate areas where additional support could be beneficial.

Table 16 presents an Analysis of Variance (ANOVA) summary comparing different assessment models based on scores of 33 students.

The Indian CBSE shows the highest average score (80.46), indicating that students tend to score higher under this model, potentially due to its grading standards or leniency in scoring. The Liverpool Grading Scheme has the lowest average score (72.66), which suggest stricter grading standards or a different emphasis in evaluation criteria. The averages of other models like the United States GPA in Percentage and Kazakhstan Assessment Model are relatively high, which are above 78, indicating generally moderate to high scoring patterns.

The Arithmetic Mean exhibits the highest variance (175.87), which indicates a wide dispersion of scores. This imply a greater diversity in student performance or less consistency in the grading system. Conversely, the United States GPA in Percentage has the lowest variance (70.68), suggesting more consistent scoring and potentially a more standardized assessment method across students. Variance in other models like the Proposed FLM and the Liverpool Grading Scheme falls in the mid-range, indicating moderate consistency and variability in scores. High variance in models such as the Arithmetic Mean necessitate a review of assessment criteria or grading practices to ensure consistency. The high mean and low variance in the Indian CBSE and United States GPA models indicate effective standardization in

Table 12. Lecture and examination grades.

#	1	2	3	4	5	6	7	CC1	CC1 all	MC1	Rat1	8	9
1	a/np	0	0	80	80	100	a/np	52	76.23	64	70.12	90	a/np
2	a/np	90	95	90	0	100	a/np	75	90.8	90	90.4	93	a/np
3	a/np	90	30	80	80	90	a/np	74	56.13	52	54.07	90	a/np
4	a/np	90	80	100	60	90	a/np	84	83.8	84	83.9	93	a/np
5	a/np	90	50	60	90	90	a/np	76	70.7	52	61.35	90	a/np
6	a/np	90	85	100	90	80	a/np	89	90.8	92	91.4	93	a/np
7	a/np	90	75	70	80	80	a/np	79	72.47	76	74.23	90	a/np
8	a/np	90	100	80	80	70	a/np	84	57.47	84	70.73	90	a/np
9	a/np	90	90	100	90	95	a/np	93	94.27	92	93.13	95	a/np
10	a/np	90	100	100	100	100	a/np	98	92.07	90	91.03	90	a/np
11	a/np	90	70	90	70	100	a/np	84	78.47	68	73.23	90	a/np
12	a/np	90	90	80	80	90	a/np	86	92.5	93	92.75	90	a/np
13	a/np	90	80	90	80	90	a/np	86	84.7	72	78.35	90	a/np
14	a/np	90	90	100	70	70	a/np	84	73.13	76	74.57	90	a/np
15	a/np	90	90	80	90	60	a/np	82	72.07	100	86.03	90	a/np
16	a/np	90	85	100	90	80	a/np	89	88.47	88	88.23	90	a/np
17	a/np	90	80	90	70	80	a/np	82	86.23	86	86.12	90	a/np
18	a/np	90	0	0	0	0	a/np	18	17.93	83	50.47	0	a/np
19	a/np	90	70	80	70	90	a/np	80	42.33	60	51.17	90	a/np
20	a/np	90	100	90	50	80	a/np	82	63.57	64	63.78	90	a/np
21	a/np	90	90	80	90	80	a/np	86	66.53	76	71.27	90	a/np
22	a/np	90	70	30	50	0	a/np	48	50.27	52	51.13	90	a/np
23	a/np	90	100	100	70	80	a/np	88	86.5	84	85.25	90	a/np
24	a/np	90	100	100	80	80	a/np	90	77.33	70	73.67	90	a/np
25	a/np	90	0	90	70	70	a/np	64	61.97	76	68.98	90	a/np
26	a/np	90	30	90	70	50	a/np	66	63.6	64	63.8	90	a/np
27	a/np	90	90	100	80	80	a/np	88	92.27	92	92.13	90	a/np
28	a/np	90	80	100	100	80	a/np	90	95.17	96	95.58	96	a/np
29	a/np	90	90	90	70	80	a/np	84	78.47	80	79.23	90	a/np
30	a/np	90	90	100	90	100	a/np	94	94.2	96	95.1	90	a/np
31	a/np	90	90	100	100	100	a/np	96	97.2	100	98.6	90	a/np
32	a/np	90	90	90	0	70	a/np	68	65.27	84	74.63	90	a/np
33	a/np	90	80	90	60	90	a/np	82	83.73	68	75.87	90	a/np
#	10	11	12	13	14	15	CC2	CC2 all	MC2	Rat2	RA	E	FG
1	80	a/np	90	90	90	a/np	88	72.04	93	82.52	76	74	75
2	70	a/np	90	90	90	a/np	86.6	80.82	88	84.41	87	80	84
3	90	a/np	90	90	90	a/np	90	58.62	65	61.81	58	50	55
4	100	a/np	90	90	90	a/np	92.6	78.96	73	75.98	80	90	84
5	70	a/np	90	90	90	a/np	86	60.95	80	70.47	66	78	71
6	100	a/np	90	90	90	a/np	92.6	91.93	90	90.97	91	90	91
7	80	a/np	90	90	90	a/np	88	55.16	70	62.58	68	86	75
8	80	a/np	90	90	90	a/np	88	63.6	85	74.3	73	73	73
9	90	a/np	90	90	90	a/np	91	94.45	88	91.22	92	95	93
10	90	a/np	90	90	90	a/np	90	86.33	80	83.16	87	90	88
11	90	a/np	90	90	90	a/np	90	74.5	88	81.25	77	86	81
12	100	a/np	90	90	90	a/np	92	92.78	90	91.39	92	95	93
13	90	a/np	90	90	90	a/np	90	81.12	73	77.06	78	65	73
14	90	a/np	90	90	90	a/np	90	58.56	78	68.28	71	70	71
15	80	a/np	90	90	90	a/np	88	73.16	85	79.08	83	70	78
16	90	a/np	90	90	90	a/np	90	87.38	85	86.19	87	95	90
17	90	a/np	90	90	90	a/np	90	82.56	70	76.28	81	90	85
18	0	a/np	90	90	90	a/np	54	41.42	60	50.71	51	50	51
19	80	a/np	90	90	90	a/np	88	50.48	62	56.24	54	50	52
20	50	a/np	90	90	90	a/np	82	73.46	68	70.73	67	86	75
21	70	a/np	90	90	90	a/np	86	66.89	80	73.44	72	73	72
22	80	a/np	90	90	90	a/np	88	62.6	83	72.8	62	85	71
23	90	a/np	90	90	90	a/np	90	83.91	85	84.46	85	90	87
24	80	a/np	90	90	90	a/np	88	78.47	90	84.24	79	88	83
25	80	a/np	90	90	90	a/np	88	81.22	75	78.11	74	74	74
26	60	a/np	90	90	90	a/np	84	85.86	60	72.93	68	88	76
27	90	a/np	90	90	90	a/np	90	89.5	91	90.25	91	95	93
28	90	a/np	90	90	90	a/np	91.2	94.8	90	92.4	94	96	95
29	90	a/np	90	90	90	a/np	90	69.69	85	77.34	78	65	73
30	60	a/np	90	90	90	a/np	84	63.92	88	75.96	86	75	82
31	90	a/np	90	90	90	a/np	90	95.25	90	92.62	96	96	96
32	90	a/np	90	90	90	a/np	90	71.69	78	74.84	75	75	75
33	90	a/np	90	90	90	a/np	90	83.38	83	83.19	80	80	80

Table 13. Laboratory grades.

#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	a/np	a/np	90	90	a/np	86	a/np	0	50	75	70	70	75	90	75
2	a/np	a/np	98	98	a/np	92	a/np	90	0	80	90	95	95	93	95
3	a/np	a/np	90	0	a/np	50	a/np	30	80	30	30	30	50	50	50
4	a/np	a/np	90	90	a/np	90	a/np	0	50	75	90	93	90	90	95
5	a/np	a/np	70	65	a/np	90	a/np	0	50	60	75	0	85	50	50
6	a/np	a/np	90	90	a/np	90	a/np	90	90	95	90	95	95	95	95
7	a/np	a/np	70	75	a/np	75	a/np	70	0	0	75	0	0	70	50
8	a/np	a/np	86	0	a/np	50	a/np	30	80	30	70	30	80	0	50
9	a/np	a/np	90	95	a/np	95	a/np	93	95	98	98	95	95	95	95
10	a/np	a/np	90	90	a/np	97	a/np	78	90	78	80	90	90	92	86
11	a/np	a/np	90	88	a/np	75	a/np	60	50	70	78	30	90	90	70
12	a/np	a/np	86	100	a/np	90	a/np	90	90	95	90	93	90	93	93
13	a/np	a/np	90	90	a/np	75	a/np	90	90	90	80	70	90	90	50
14	a/np	a/np	70	70	a/np	90	a/np	70	50	0	0	0	73	75	75
15	a/np	a/np	76	60	a/np	90	a/np	65	80	65	75	78	90	50	50
16	a/np	a/np	95	86	a/np	90	a/np	93	95	95	95	95	96	95	98
17	a/np	a/np	90	86	a/np	90	a/np	70	75	75	90	90	95	95	95
18	a/np	a/np	0	0	a/np	50	a/np	30	0	0	30	30	50	0	50
19	a/np	a/np	0	0	a/np	50	a/np	30	0	0	30	30	50	0	50
20	a/np	a/np	80	0	a/np	86	a/np	75	90	50	50	90	82	90	50
21	a/np	a/np	95	0	a/np	90	a/np	30	80	30	70	30	85	90	50
22	a/np	a/np	86	0	a/np	50	a/np	50	50	50	70	60	70	0	70
23	a/np	a/np	90	90	a/np	90	a/np	75	90	85	90	90	90	90	75
24	a/np	a/np	90	80	a/np	90	a/np	75	95	78	50	90	90	90	70
25	a/np	a/np	0	70	a/np	90	a/np	75	80	75	80	90	90	93	75
26	a/np	a/np	90	0	a/np	75	a/np	75	90	80	90	90	90	90	86
27	a/np	a/np	90	98	a/np	95	a/np	90	90	78	90	90	90	95	95
28	a/np	a/np	96	98	a/np	95	a/np	95	95	98	98	95	98	95	95
29	a/np	a/np	75	70	a/np	90	a/np	0	0	78	70	70	90	90	93
30	a/np	a/np	100	95	a/np	90	a/np	80	50	0	30	30	70	90	50
31	a/np	a/np	100	100	a/np	100	a/np	98	98	98	100	95	95	98	98
32	a/np	a/np	70	80	a/np	70	a/np	80	50	70	80	75	0	50	70
33	a/np	a/np	80	90	a/np	90	a/np	75	70	85	80	70	90	90	90

Table 14. Student's self work grades.

#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	a/np	a/np	70	70	a/np	75	a/np	50	90	75	a/np	90	a/np	a/np	a/np
2	a/np	a/np	90	88	a/np	100	a/np	85	90	50	a/np	90	a/np	a/np	a/np
3	a/np	a/np	60	60	a/np	60	a/np	50	70	50	a/np	80	a/np	a/np	a/np
4	a/np	a/np	90	70	a/np	60	a/np	50	90	90	a/np	90	a/np	a/np	a/np
5	a/np	a/np	60	60	a/np	60	a/np	50	75	70	a/np	80	a/np	a/np	a/np
6	a/np	a/np	90	90	a/np	100	a/np	75	90	100	a/np	93	a/np	a/np	a/np
7	a/np	a/np	70	70	a/np	60	a/np	50	90	50	a/np	90	a/np	a/np	a/np
8	a/np	a/np	60	60	a/np	60	a/np	75	90	50	a/np	90	a/np	a/np	a/np
9	a/np	a/np	95	95	a/np	100	a/np	100	90	100	a/np	90	a/np	a/np	a/np
10	a/np	a/np	88	75	a/np	100	a/np	86	90	75	a/np	90	a/np	a/np	a/np
11	a/np	a/np	60	60	a/np	75	a/np	50	90	75	a/np	90	a/np	a/np	a/np
12	a/np	a/np	100	93	a/np	100	a/np	100	90	100	a/np	90	a/np	a/np	a/np
13	a/np	a/np	75	85	a/np	90	a/np	70	90	50	a/np	90	a/np	a/np	a/np
14	a/np	a/np	60	60	a/np	60	a/np	50	75	50	a/np	80	a/np	a/np	a/np
15	a/np	a/np	60	60	a/np	60	a/np	50	90	50	a/np	90	a/np	a/np	a/np
16	a/np	a/np	90	75	a/np	90	a/np	50	95	50	a/np	95	a/np	a/np	a/np
17	a/np	a/np	90	75	a/np	90	a/np	50	95	50	a/np	95	a/np	a/np	a/np
18	a/np	a/np	0	0	a/np	60	a/np	50	70	50	a/np	80	a/np	a/np	a/np
19	a/np	a/np	60	60	a/np	60	a/np	50	90	50	a/np	90	a/np	a/np	a/np
20	a/np	a/np	60	60	a/np	75	a/np	50	90	50	a/np	90	a/np	a/np	a/np
21	a/np	a/np	60	60	a/np	65	a/np	75	70	50	a/np	80	a/np	a/np	a/np
22	a/np	a/np	60	60	a/np	60	a/np	50	70	50	a/np	80	a/np	a/np	a/np
23	a/np	a/np	75	89	a/np	75	a/np	78	90	50	a/np	90	a/np	a/np	a/np
24	a/np	a/np	80	0	a/np	80	a/np	50	90	50	a/np	90	a/np	a/np	a/np
25	a/np	a/np	65	70	a/np	90	a/np	70	90	50	a/np	90	a/np	a/np	a/np
26	a/np	a/np	60	89	a/np	80	a/np	75	90	90	a/np	90	a/np	a/np	a/np
27	a/np	a/np	85	90	a/np	100	a/np	90	80	95	a/np	90	a/np	a/np	a/np
28	a/np	a/np	95	95	a/np	100	a/np	100	90	100	a/np	90	a/np	a/np	a/np
29	a/np	a/np	50	75	a/np	100	a/np	50	90	50	a/np	90	a/np	a/np	a/np
30	a/np	a/np	89	90	a/np	100	a/np	90	75	50	a/np	80	a/np	a/np	a/np
31	a/np	a/np	90	90	a/np	100	a/np	100	90	100	a/np	90	a/np	a/np	a/np
32	a/np	a/np	50	50	a/np	50	a/np	75	80	75	a/np	90	a/np	a/np	a/np
33	a/np	a/np	80	70	a/np	90	a/np	75	90	75	a/np	90	a/np	a/np	a/np

Table 15. Assessment results by various models.

Student/ model	Kazakhstan assessment model	Arithmetic mean	Liverpool Grading Scheme	United States GPA in percentage	Indian CBSE	Chinese GPA	Proposed Fuzzy Logic Model
1	75	71.206897	66.97662338	77	79.16	71.65584416	73.5
2	84	83	74.37792208	85	89.15	81.96597403	82.91
3	55	61.724138	55.96233766	68	63.93	59.10649351	60.62
4	84	81.586207	78.31168831	82	84.5	84.46792208	82.48
5	71	66.827586	67.92207792	73	71.78	70.42727273	70.16
6	91	91.413793	83.42857143	91	91.41	91.0361039	89.88
7	75	65.034483	69.11038961	76	75.44	70.93441558	71.92
8	73	66.344828	64.22727273	76	71.26	68.42857143	69.88
9	93	94.103448	84	96	94.1	94.14415584	92.56
10	88	89.482759	83.17532468	88	89.48	90.03766234	88.03
11	81	77.482759	76.27922078	78	77.48	80.61558442	78.48
12	93	92	83	92	92	92.35974026	90.72
13	73	82.758621	76.68181818	82	82.76	78.43896104	79.27
14	71	67.172414	67.73376623	72	74.92	68.94155844	70.29
15	78	74.448276	71.96753247	74	74.45	74.31688312	74.53
16	90	88.551724	82.85714286	87	88.55	91.30844156	88.04
17	85	84.344828	80.44805195	83	84.34	86.52207792	83.94
18	51	33.103448	30.6	59	60	36.77402597	45.08
19	52	54.827586	53.78571429	67	66.25	53.31688312	57.86
20	75	73.241379	72.96753247	76	75.86	77.44935065	75.08
21	72	70.448276	67.62987013	75	72.96	71.9987013	71.67
22	71	60.37931	61.17142857	68	67.35	67.20649351	65.85
23	87	85.586207	81.54545455	85	85.59	87.55974026	85.38
24	83	79.862069	79.36753247	81	82.71	83.87662338	81.64
25	74	75.068966	71.08571429	79	80.63	74.80909091	75.77
26	76	78.206897	72.35194805	80	81	80.44545455	78
27	93	90.206897	82.7012987	89	90.21	91.5	89.44
28	95	94.137931	83	92	94.14	94.40597403	92.11
29	73	74.689655	72.07142857	78	80.22	72.61428571	75.1
30	82	76.689655	71.84415584	79	79.43	76.08181818	77.51
31	96	95.37931	84	92	95.38	95.58311688	93.06
32	75	70	69.27402597	74	75.19	71.86883117	72.55
33	80	83.448276	78.05194805	84	83.45	82.76103896	81.95

Table 16. ANOVA summary.

Groups	Count	Sum	Average	Variance
Kazakhstan assessment model	33	2595	78.63636	130.9886
Arithmetic mean	33	2532.759	76.75026	175.8725
Liverpool Grading Scheme	33	2397.908	72.66387	122.498
United States GPA in percentage	33	2638	79.93939	70.68371
Indian CBSE	33	2655.08	80.45697	83.69001
Chinese GPA	33	2572.959	77.96846	163.9049
Proposed Fuzzy Logic Model	33	2565.26	77.73515	116.3269

these grading systems, which might be beneficial for maintaining equity in student evaluation. Models with lower means and higher variance need to reevaluate the balance between assessment rigor and fairness to ensure that the grading system accurately reflects student abilities without undue harshness. Table 16 provides insightful initial data on how various international grading models compare in terms of average performance and consistency of student scores. These insights guide educational institutions in aligning their assessment practices with those that demonstrate the best outcomes in terms of fairness, consistency and reflective capability of student performance. Further statistical testing would clarify the extent of these differences and help in making informed decisions regarding assessment standards.

Table 17 presents the results of an ANOVA test conducted to compare the mean scores across different grading models as previously summarized in Table 16.

The F-statistic of 1.774525 indicates the ratio of the variance explained by the group means to the variance within the groups. A *p* value of .105328 suggests that there is a 10.5328% chance of observing such an F-statistic if the null hypothesis were true, ie if no significant difference existed between the group means. The F-statistic is below the critical *F*-value (*F* crit) of 2.13921. This means that the observed F-statistic is not large enough to reject the null hypothesis at a common alpha level of 0.05 (5% significance level). Consequently, this ANOVA result suggests that there are no statistically

Table 17. ANOVA test.

Source of variation	*SS*	*df*	*MS*	*F*	*p* Value	*F crit*
Between groups	1314.109	6	219.0181	1.774525	.105328	2.13921
Within groups	27,646.87	224	123.4235			

significant differences between the average scores provided by the seven assessment models at the 5% significance level. This finding implies that, on average, no one model is significantly more lenient or strict than the others when considering the overall group. Since no significant differences were found among the grading models, educational institutions might consider that these models, though derived from different cultural and educational frameworks, provide consistent assessments when viewed across a diverse student body. This uniformity imply that any of these models could be used interchangeably without expecting statistically significant disparities in student performance outcomes. However, individual characteristics of each model, such as specific strengths in fairness, cultural adaptability and methodological rigor, should still be considered in the decision-making process. Table 17 provides valuable insights into the comparability of different grading models in assessing student performance. The lack of significant differences suggests that these models are similarly rigorous and could be suitable for diverse educational contexts. However, further detailed studies could enhance understanding of these models' implications in specific educational settings or among particular student demographics.

Discussion

Figure 3 displays the correlation coefficients between various grading models used to assess student performance.

The correlation coefficients in Figure 3 range from near perfect correlation (values close to 1) to high correlation (values above 0.89). All models show strong correlations with each other, with the lowest correlation coefficient being 0.897 between the Liverpool Grading Scheme and the Indian CBSE. This high level of correlation suggests that despite different methodologies and cultural contexts, these grading models broadly agree on student performance rankings. The FLM shows exceptionally high correlations with all other models, particularly with the China GPA (0.993) and AVG (Arithmetic Mean, 0.990). This indicates that the FLM integrates aspects that are very consistent with how the Arithmetic Mean and Chinese educational assessments evaluate student performance. The strong correlation between the U.S. GPA and CBSE (0.980) could suggest that both systems were using similar scales or value similar academic attributes, despite geographical and systemic differences. The lower correlation between the Liverpool Grading Scheme and the CBSE (0.897) indicated differing priorities in academic evaluation or differing emphases on assessment criteria between UK-based and Indian educational systems. The high correlation of the FLM with all traditional models suggests that it successfully captures the essence of student performance as traditionally measured. This success advocate for its broader adoption if it also offers other advantages, such as adaptability, ease of interpretation, or greater fairness in handling borderline cases. Figure 3 effectively illustrates that while educational assessment models can vary widely in their approach and geographical origin, they often agree substantially on how students are ranked. This cross-model agreement validates the general reliability of these models. The particularly high performance of the FLM in aligning with established models suggests its potential utility in educational settings.

In this paper, our research group make a compelling case for adopting fuzzy logic in the assessment of student performance, which has significant implications for policymakers and educators. We argue that traditional grading systems often fail to capture the nuanced capabilities of students, leading to potential inaccuracies and unfairness in student evaluations. The introduction of a FLM addresses these issues by incorporating flexibility and a broader consideration of student performance factors, making the assessment process more equitable and comprehensive. We suggest that policymakers should consider integrating fuzzy logic into educational assessment frameworks to enhance the fairness and accuracy of student evaluations. This approach allows for a more individualized assessment strategy, which is

Models	KAZ	AVG	Liv	US GPA	CBSE	China GPA	Fuzzy
KAZ	1	0.929201	0.915567	0.931849	0.934063	0.962114	0.9673382
AVG	0.929201	1	0.969656	0.965094	0.953112	0.983862	0.9898714
Liv	0.915567	0.969656	1	0.907814	0.897054	0.97784	0.9698771
US GPA	0.931849	0.965094	0.907814	1	0.979744	0.9524	0.9746936
CBSE	0.934063	0.953112	0.897054	0.979744	1	0.941458	0.968848
China GPA	0.962114	0.983862	0.97784	0.9524	0.941458	1	0.9936861
Fuzzy	0.967338	0.989871	0.969877	0.974694	0.968848	0.993686	1

Figure 3. Correlation of different assessment models.

crucial in diverse educational environments where students exhibit varied learning styles and competencies. Moreover, the use of fuzzy logic can help in reducing biases inherent in human evaluations, offering a more objective basis for grading. Educators are encouraged to adopt this new model as it provides a richer, more detailed understanding of student performance. By doing so, educators can better identify areas where students may need additional support, tailor their teaching strategies to meet individual needs and ultimately improve educational outcomes. The findings of this study are particularly interesting as they demonstrate that the FLM can outperform traditional grading systems in terms of fairness and representativeness of student achievements. This contributes significantly to the literature by providing a practical example of how advanced computational techniques can be applied in educational settings to solve longstanding issues related to assessment.

Conclusion

This research comprehensively evaluates various assessment models within educational systems, focusing on the innovative application of fuzzy logic alongside traditional methods. The study reveals that fuzzy logic provides a flexible, nuanced approach to student assessment, capable of handling the subtleties and variabilities inherent in educational evaluations. The analysis, involving a comparative study of traditional and fuzzy logic models across a diverse cohort of students, indicates that fuzzy logic can integrate well with existing assessment frameworks while potentially enhancing fairness and accuracy. The results underscore that no single assessment model significantly outperforms others in terms of leniency or strictness, suggesting that educational institutions can choose among these models based on other factors such as cultural relevance, ease of implementation and alignment with educational goals. The fuzzy logic model, in particular, shows high compatibility with various international grading standards, highlighting its robustness and adaptability. The strong correlation observed between fuzzy logic and other models further validates its efficacy, demonstrating that it does not diverge from conventional assessment outcomes but rather complements them by addressing ambiguities more effectively. This makes fuzzy logic an attractive option for educational systems looking to innovate and improve their assessment strategies without deviating from established norms. Overall, the study advocates for the broader adoption of fuzzy logic in educational assessments, presenting it as a method that not only matches but potentially surpasses traditional models in handling complex, multifaceted educational scenarios. As educational paradigms evolve, embracing such advanced assessment techniques will be crucial in accurately and fairly evaluating student performance, thus better preparing learners for the challenges of the modern world. In constructing the FLM for assessing student performance, the research group acknowledges several limitations that need to be addressed. The study was conducted on a relatively small and homogenous sample of 33 students from specific courses in Kazakhstan, which may limit the generalizability of the findings to other educational contexts or larger and more diverse student populations. The specificity of the sample constrains the broad applicability of the results, and further research is needed to validate the FLM across different disciplines and educational settings. Integrating a new assessment model like FLM within existing educational frameworks can face resistance from stakeholders accustomed to traditional grading systems. The shift to a fuzzy logic-based system requires not only logistical changes but also a change in mindset about how student performance is evaluated, which may be met with skepticism or resistance. To mitigate these limitations, future research should focus on expanding the sample size and diversity, simplifying the implementation of fuzzy systems for educational use and conducting extensive training sessions for educators and administrators. Further studies should also explore the development of standardized guidelines for setting input variables and membership functions to enhance the reliability and objectivity of the FLM.

Authors note

The research team behind this study is affiliated with the Faculty of Information Technologies at L.N. Gumilyov Eurasian National University, Kazakhstan. Our primary research focuses on innovative educational technologies, artificial intelligence applications in education and computational models for student assessment. This study on fuzzy logic-based grading models aligns with our broader research efforts aimed at improving fairness and consistency in student evaluation systems. By leveraging fuzzy inference systems, we aim to enhance the accuracy of performance assessments, ensuring a more equitable grading process in educational institutions. Our work is part of a larger initiative exploring adaptive learning, machine learning models in education and automated decision-support systems. Through interdisciplinary collaboration, we strive to develop tools that support data-driven educational policies and personalized learning experiences, contributing to the advancement of modern education.

Disclosure statement

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