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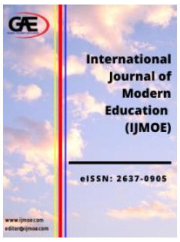

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A FUZZY LOGIC APPROACH TO PREDICTING STUDENTS' MATHEMATICS PERFORMANCE

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Abstract:

Mathematics performance plays a vital role in academic success; however, recent trends indicate a decline, especially among science students. Three factors that may contribute to the students' performance in Calculus I are attendance, test scores, and study hours. This study proposes a predictive model based on Fuzzy Logic to assess the mathematics performance of Universiti Teknologi MARA (UiTM) students in Calculus I. Developed using MATLAB, the model integrates three primary input variables; attendance, study hours, and test scores are selected for their significant impact on academic achievement as established in prior studies. Data was collected from students in the Faculty of Applied Sciences (FSG) and the College of Computing, Informatics, and Mathematics (KPPIM) at the UiTM Perlis Branch. The model was validated and found to reliably predict student performance. Among the variables, test scores emerged as the most significant predictor, highlighting their potential as an early indicator for identifying students at risk of underperforming. These insights can assist lecturers in implementing timely, targeted interventions to support academic improvement. In conclusion, the Fuzzy Logic model provides an effective, data-driven approach for predicting mathematics performance. It offers valuable support for educators seeking to enhance student outcomes in mathematics-related courses.

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Keywords:

Fuzzy Logic, Mathematics Performance, Predictive Modelling, Academic Achievement, MATLAB, Higher Education

Introduction

Mathematics is a fundamental subject in education, especially in fields like engineering, science, and technology. It fosters logical thinking, problem-solving, and mental discipline, which are essential skills for academic and career success. Mathematics helps students understand and apply concepts in areas such as budgeting, decision-making, and critical thinking, making it an important part of daily life and education. Despite its importance, interest in mathematics among students in Malaysia has been steadily declining. The Ministry of Education has acknowledged this issue and is working to make mathematics more engaging and relevant to students. However, recent statistics reveal a worrying trend. According to the Malaysia Examination Board, the 2022 SPM results showed that Additional Mathematics and Mathematics had the highest failure rates among all subjects, 26.2% and 24.3% respectively. This decline in performance reflects a larger problem that needs urgent attention.

A student's performance in mathematics is influenced by a wide range of factors, including study habits, attendance, self-confidence, learning strategies, and support from teachers and peers. Positive behaviours such as regular attendance and active participation are linked to better academic outcomes, while negative behaviours like absenteeism and lack of motivation can lead to failure. Additionally, attitudes toward mathematics, classroom dynamics, and the availability of academic support services can also play a significant role in shaping mathematical performance. Mathematics performance refers to a student's ability to understand and apply mathematical concepts, usually measured through test scores and academic results. Predicting mathematics performance is important because it allows educators to identify struggling students early and provide the necessary support to help them improve. By using predictive tools, educators can effectively design their instructional strategies and implement targeted interventions to support and improve student learning outcomes.

One powerful and effective tool for this purpose is the Fuzzy Logic system, a mathematical model that can handle uncertain or imprecise data. Unlike traditional methods, fuzzy logic can interpret a range of input values such as attendance, study hours, and test scores and make more accurate predictions about student performance. This method is particularly useful in educational settings where many influencing factors cannot be precisely measured. This study focuses on students at UiTM Arau, Perlis, where many programs include at least one mathematics course, such as Calculus I (MAT183). The study aims to predict the mathematics performance of diploma students using fuzzy logic, based on three key factors: attendance, study hours, and test scores. The selected programs for this study include the Diploma in Mathematical Sciences (CDCS143), Diploma in Science (AS120), and Diploma in Technology Chemical Industry (AS125). Data was collected through online surveys and lecturer interviews. The findings of this study can benefit students, lecturers, and the university. For students, it provides insights into their academic standing and highlights areas for improvement before final exams. For lecturers, it helps in refining teaching strategies and identifying students who may need extra support. For the university, this study contributes to enhancing student academic performance, reducing course failure rates, and supporting on-time graduation. These

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improvements not only benefit individual students but also strengthen the institution's overall reputation and help achieve academic performance benchmarks. However, the study is limited to UiTM Arau students who are taking Calculus I for the first time and focuses on only three performance-related factors. As such, the findings may not be fully generalizable to other campuses or student populations. Future research could broaden the scope by including more diverse student groups, additional academic disciplines, and a wider range of influencing variables to provide a more comprehensive and inclusive analysis.

Literature Review

Predicting and evaluating mathematics performance is crucial in educational research, particularly in institutions like UiTM (Ali et al., 2009). Understanding these factors can enhance student outcomes, inform teaching strategies, and align with institutional goals of academic excellence and career preparation (Maass et al., 2019; Silangan et al., 2023). Mathematics serves as a foundation for analytical thinking, problem-solving, and reasoning, which are essential across disciplines. The study aims to support curriculum development and improve teaching methods to help students better understand mathematics at UiTM. Performance in mathematics is shaped by various factors, including attendance, study habits, classroom environment, and prior academic achievement. These elements not only influence academic success but also impact motivation, engagement, and confidence (Ismail & Idris, 2021).

Mathematics Performance and Influencing Factors

Assessment, whether it is in formative and summative, is key to evaluating learning progress. Timely feedback allows students to address weaknesses, while a positive attitude toward mathematics encourages greater persistence and engagement (Peteros et al., 2019; (Ismail & Idris, 2021). A supportive classroom atmosphere, including manageable class sizes and strong peer relationships, is essential (Nor et al., 2021). Parental support and socioeconomic status also significantly affect student performance, with limited resources often creating barriers to learning (Saturday & Onuodu, 2019). A well-structured curriculum that considers prior knowledge and real-world application improves comprehension and relevance (Gran et al., 2021). This study focuses on three key predictors: attendance, study hours, and prior mathematics performance.

Study Hours

The number and quality of study hours are consistently linked to academic achievement in mathematics (Liu, 2022; Acharya et al., 2019). Effective time management enables students to master complex concepts and develop confidence. Research shows that students who spend more time studying, especially using active learning strategies, perform better and develop a stronger self-concept, which positively influences motivation and academic perseverance (Lieberman & Remedios, 2007; Crede et al., 2008; Peteros et al., 2019). Fuzzy logic models have been used to illustrate the subtle influence of study habits on performance, showing that personalized learning plans and efficient study techniques can enhance outcomes (Salam et al., 2018; Idris et al., 2022).

Prior Mathematics Achievement

Past mathematics performance is a strong predictor of future success due to the cumulative nature of mathematical learning (Peteros et al., 2019; Moon et al., 2022). Students with solid prior knowledge tend to have higher confidence, motivation, and resilience in solving new

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problems (Marsh & Martin, 2011). Early support, formative assessments, and remediation programs can bridge learning gaps and prevent long-term academic struggles (Balfanz et al., 2007; Black & Wiliam, 1998). Research using fuzzy logic has confirmed that previous achievement significantly influences current performance (Petra & Aziz, 2021; Bhardwaj et al., 2021). This reinforces the importance of continuous monitoring and support based on earlier academic results.

Attendance Rate

Attendance plays a vital role in academic performance, particularly in sequential subjects like mathematics (Ancheta et al., 2021). Regular attendance allows students to participate actively, receive timely feedback, and build foundational knowledge (Gottfried, 2010). In contrast, absenteeism can cause learning gaps, reduce engagement, and hinder overall academic achievement. Students who attend classes consistently are more likely to follow structured study plans and engage in collaborative learning, improving class dynamics and individual outcomes (Epstein & Sheldon, 2002; Chen & Lin, 2008). Strategies such as tracking attendance, involving parents, and offering support services can mitigate absenteeism (Balfanz & Byrnes, 2012). Alongside attendance, continuous assessments like weekly tests and assignments are crucial in monitoring mathematics performance (Acharya et al., 2019).

Fuzzy Logic Method and Its Application in Student Performance Assessment

Fuzzy logic, introduced by Lotfi Zadeh in 1965, is a mathematical framework that manages uncertainty and imprecision by allowing elements to belong to sets with varying degrees of membership (Zadeh, 2015). Unlike binary logic, fuzzy logic supports nuanced reasoning, making it ideal for applications like decision-making, control systems, and artificial intelligence. Its flexibility makes it suitable for evaluating complex data, such as online reviews (Nilashi et al., 2019) and educational performance. In educational contexts, especially in assessing mathematics performance, fuzzy logic addresses the limitations of conventional statistical methods by incorporating partial truths rather than absolute values. It enables a more comprehensive evaluation by integrating variables such as attendance, assignments, weekly assessments, and psychological factors like motivation and self-concept (Petra & Aziz, 2021; Nor et al., 2021).

Fuzzy logic systems typically involve three key components: **fuzzification** (converting inputs into linguistic variables), **inference** (applying “IF-THEN” rules), and **defuzzification** (producing a crisp output). These tools allow for more accurate assessment of student performance through a holistic approach (Ismail & Idris, 2021). For instance, studies have shown that using fuzzy inference systems (FIS) can effectively assess academic performance based on multiple inputs such as test scores, attendance, and behavior (Acharya et al., 2019).

Applications of fuzzy logic in educational research are growing. At Parul University, fuzzy logic was used to classify students' performance in Engineering Mathematics into categories such as “poor” or “excellent” using Mamdani inference and trapezoidal membership functions. The results were more accurate and equitable compared to traditional grading systems (Aziz et al., 2019). Similarly, other studies have used fuzzy logic to combine continuous assessments with final exams, promoting fairer evaluations (Saturday & Onuodu, 2019). Moreover, fuzzy models have shown effectiveness in evaluating final-year student projects by incorporating inputs like technical report quality and defense presentation scores. These methods allow for

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detailed differentiation between students' performance, something traditional systems often overlook (Salam et al., 2018).

Overall, fuzzy logic enhances educational assessment by offering a flexible, data-driven, and psychologically sensitive approach. It is especially useful for evaluating mathematics performance where multiple, often ambiguous, variables are involved. As teaching strategies become increasingly learner-centered, fuzzy logic offers a promising tool for improving learning outcomes and fairness in academic evaluations.

Methodology

Data Collection

For data collection in this study, emphasis has been placed on three input factors: study hours, attendance, and test scores. The data were collected systematically from a sample of 45 students. This sample includes 30 students from two programs under the Faculty of Applied Sciences (FSG); 15 students from the Diploma in Science (AS120) program and 15 students from the Diploma in Technology (Chemical Industry) (AS125) program. The remaining 15 students are from the Faculty of Computer Science and Mathematics (FSKM), specifically the Diploma in Mathematical Sciences (CDCS143) program.

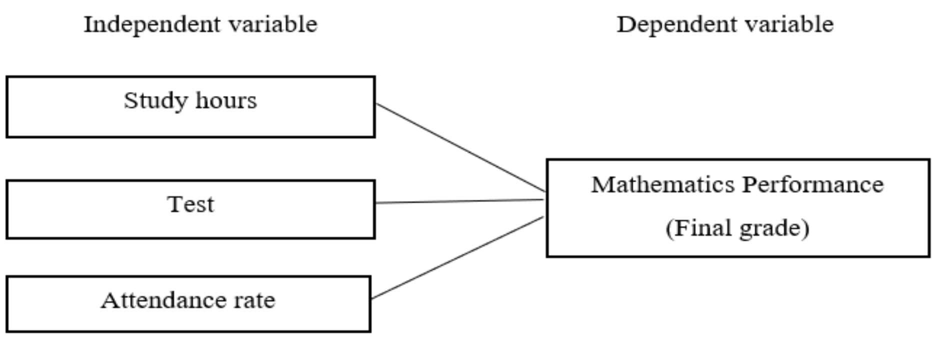

Figure 1: Independent and Dependent Variable

Figure 1 shows the connection between the independent variables (Study hours, test scores and attendance rate) as inputs and dependent variable (mathematics performance) as an output.

Data Analysis

In this study, fuzzy logic was applied in predicting mathematics performance based on chosen factors. This method is an approach based on fuzzy set theory, where truth values were expressed in degrees of truth rather than the traditional binary, true or false. Mathematics performance prediction with fuzzy logic involves five stages as shown in Figure 2.

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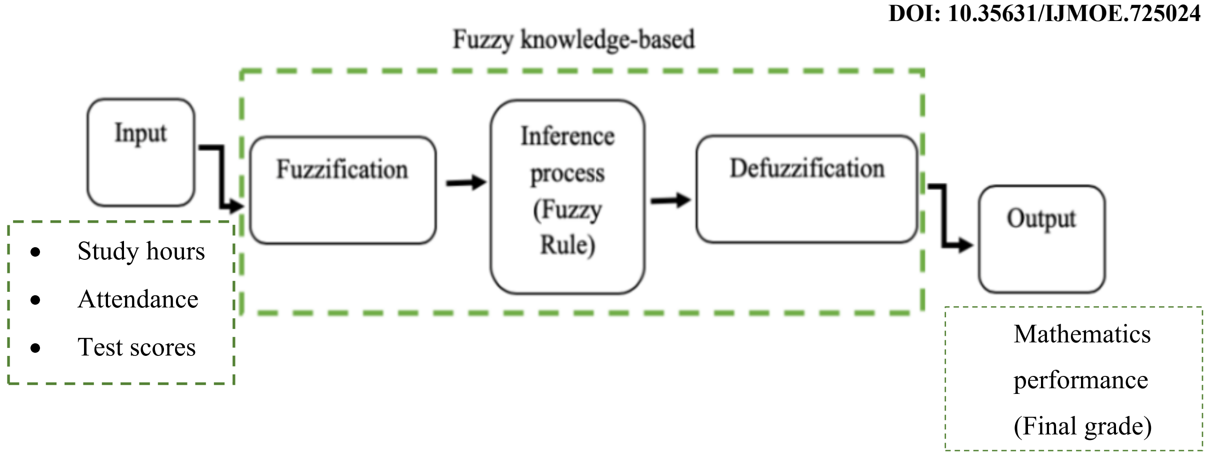

Figure 2: The Stages of Fuzzy Logic Evaluation

Stage 1: Input (Crisp Value)
Crisp values were the initial data collected from students, including the test scores obtained by the students in the semester examination, attendance and study hours.

Stage 2: Fuzzification
The fuzzification process consist of 2 steps.

Step 1: Setup And Identify All The Inputs And Output For The Linguistic Variables.
Fuzzification of mathematics performance was carried out using input variables and their membership functions. These linguistic variables are also represented by fuzzy numbers. There are three inputs: study hours, attendance, and test scores. The output is obtained from the final grade as the mathematics performance. Table 1 shows the linguistic variables, symbol, fuzzy numbers, and associated range for each input and output for the system. The input data for this study was converted by normalizing the hours of study per day to a range of 0 to 8, scaling the student attendance percentage from 0 to 100% to a range of 0 to 5, and adjusting the test scores, originally out of 40 marks, to a range of 0 to 20. This standardization enabled easier comparison and analysis across different data points.

Table 1: Linguistic Variables And Their Fuzzy Numbers

Name of The Inputs and Output		**Linguistic Variables**	**Symbol**	**Fuzzy Numbers**	**Range**
Input	**Hours of study per day** (Salam et al., 2018)	Very Low	VL	(0,0.5,1.5)	[0,8]
		Low	L	(1,2,2.5)	
		Moderate	M	(2,3,3.5)	
		High	H	(3,4,5)	
		Very High	VH	(4.5,6,8)	
	Attendance (Acharya et al., 2019)	Very Poor	VP	(0,0,2)	[0,5]
		Poor	P	(0,1.5,3)	
		Good	G	(2,3,4)	
		Very Good	VG	(3,4,5)	
		Excellent	E	(4,5,5)	
	Test (Acharya et al., 2019)	Very Poor	VP	(0,0,8)	[0,20]
		Poor	P	(0,6,12)	
		Good	G	(8,12,16)	
		Very Good	VG	(12,16,20)	
		Excellent	E	(16,20,20)	
Output		Fail	F	(0,0,49)	[0,100]

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Mathematics Performance (Final grade)	Pass	P	(47,60,69)
	Good	G	(65,75,79)
	Excellent	E	(70,85,89)
	Outstanding	O	(85,95,100)

Step 2: Develop Membership Functions For Each Input And Output Of The Linguistic Variable.

This step involves creating the membership function for each set of the linguistic variables. The membership function was generated using a triangular fuzzy number. The input data and the output are categorized into several linguistic variables before the membership value was assigned to each of them. Table 2 shows an input data of hours of study per day as an example. The data were classified into five categories.

Table 2: Categories And Range For The Hours Of Study Per Day

Categories	Range
Very Low	$0 \leq x \leq 1.5$
Low	$1 \leq x \leq 2.5$
Moderate	$2 \leq x \leq 3.5$
High	$3 \leq x \leq 5$
Very High	$4.5 \leq x \leq 8$

The membership function of the hours of study per day are shown below.

$$\mu_{Very\ Low}(x) = \begin{cases} \dfrac{x}{0.5}; & 0 \leq x \leq 0.5 \\ 1.5 - x; & 0.5 \leq x \leq 1.5 \\ 0; & otherwise \end{cases}$$

$$\mu_{Low}(x) = \begin{cases} x - 1; & 1 \leq x \leq 2 \\ \dfrac{2.5 - x}{0.5}; & 2 \leq x \leq 2.5 \\ 0; & otherwise \end{cases}$$

$$\mu_{Moderate}(x) = \begin{cases} x - 2; & 2 \leq x \leq 3 \\ \dfrac{3.5 - x}{0.5}; & 3 \leq x \leq 3.5 \\ 0; & otherwise \end{cases}$$

$$\mu_{High}(x) = \begin{cases} x - 3; & 3 \leq x \leq 4 \\ 5 - x; & 4 \leq x \leq 5 \\ 0; & otherwise \end{cases}$$

$$\mu_{Very\ High}(x) = \begin{cases} \dfrac{x - 4.5}{1.5}; & 4.5 \leq x \leq 6 \\ \dfrac{8 - x}{2}; & 6 \leq x \leq 8 \\ 0; & otherwise \end{cases}$$

The output in the form of the mathematics performance (final grade) was categorized as fail, pass, good, excellent and outstanding. Table 3 shows the ranges of marks obtained from each category.

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Table 3: Categories and Range of Mathematics Performance (Final Grade)

Categories	Range
Fail	$0 \leq x \leq 49$
Pass	$47 \leq x \leq 69$
Good	$65 \leq x \leq 79$
Excellent	$70 \leq x \leq 89$
Outstanding	$85 \leq x \leq 100$

The equation presented below demonstrates the method for determining the membership function associated with the five categories the mathematics performance (final grade).

$$\mu_{Fail}(x) = \begin{cases} \dfrac{49 - x}{49}; & 0 \leq x \leq 49 \\ 0; & otherwise \end{cases}$$

$$\mu_{Pass}(x) = \begin{cases} \dfrac{x - 47}{13}; & 47 \leq x \leq 60 \\ \dfrac{69 - x}{9}; & 60 \leq x \leq 69 \\ 0; & otherwise \end{cases}$$

$$\mu_{Good}(x) = \begin{cases} \dfrac{x - 65}{10}; & 65 \leq x \leq 75 \\ \dfrac{79 - x}{4}; & 75 \leq x \leq 79 \\ 0; & otherwise \end{cases}$$

$$\mu_{Excellent}(x) = \begin{cases} \dfrac{x - 70}{15}; & 70 \leq x \leq 85 \\ \dfrac{89 - x}{4}; & 85 \leq x \leq 89 \\ 0; & otherwise \end{cases}$$

$$\mu_{Outstanding}(x) = \begin{cases} \dfrac{x - 85}{10}; & 85 \leq x \leq 95 \\ \dfrac{100 - x}{5}; & 95 \leq x \leq 100 \\ 0; & otherwise \end{cases}$$

Stage 3: Inference Process (Fuzzy Rule Based)
There are 3 steps in this process.

Step 1: Set Up The Fuzzy Rule Base
The fuzzy rule-based approach involved defining a set of fuzzy rules, typically in the form of "If-Then" statements, to predict mathematics performance. This consisted of a set of if-then rules that define how the input variables were related to the output variables. These rules were derived from expert knowledge or empirical data and capture the relationships between inputs and outputs while handling uncertainty. Each rule evaluated the degree to which the fuzzy inputs satisfy the conditions, and the combined output from all applicable rules formed the basis for the final prediction. Table 4 shows the list of some fuzzy rules for input variables and output. There are 125 Fuzzy IF-THEN Rule are formed.

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Table 4: List of Fuzzy Rules of Attendance, Study Hours, Test Scores, and Mathematics Performance

Rule	IF Attendance is	AND Study Hours are	AND Test Scores are	THEN Mathematics performance is
1	Very Poor	Very Poor	Very Poor	Fail
2	Very Poor	Very Poor	Poor	Fail
3	Very Poor	Very Poor	Good	Pass
4	Very Poor	Very Poor	Very Good	Satisfactory
5	Very Poor	Very Poor	Excellent	Good
6	Very Poor	Poor	Very Poor	Fail
7-12	…	…	…	…
13	Very Low	Excellent	Very Good	Excellent
14-124	…	…	…	…
125	Excellent	Excellent	Excellent	Excellent

Step 2: Conversion Of Crisp Data To Fuzzy Data Sets Using Membership Functions.
In the process of fuzzification, numerical input variables undergo a conversion into their respective fuzzy sets through the utilization of membership function. Let's consider the crisp inputs for study hours per day, attendance, and test score to be 0.2, 5, and 16 respectively.
Input value: [0.2 5 16]. The conversion calculation into fuzzy data set is shown in Table 5.

Table 5: Conversion Of Crisp Data Into Fuzzy Data Sets

Study hours per day				
Very Low	Low	Moderate	High	Very High
$\frac{x}{0.5} = \frac{0.2}{0.5} = 0.4$	0	0	0	0
Attendance				
Very Poor	Poor	Good	Very Good	Excellent
0	0	0	$5 - x = 5 - 5 = 0$	$x - 4 = 5 - 4 = 1$
Test score				
Very Poor	Poor	Good	Very Good	Excellent
0	0	$= \frac{16 - x}{4} = \frac{16 - 16}{4} = 0$	$= \frac{x - 12}{4} = \frac{16 - 12}{4} = 1$	$= \frac{x - 16}{4} = \frac{16 - 16}{4} = 0$

Step 3: Evaluate Rules In The Fuzzy Rule Based And Combine Results From Each Rule.
Let w = study hours per day, x = attendance, y = test score, and z = mathematics performance. Suppose that for $w = 0.2$, $x = 5$, $y = 16$ then the combination of the fuzzy inputs with the rules in fuzzy rules based is illustrated in Figure 3. The graphs are generated from MATLAB. There is one Fuzzy Rule Based that resulting the membership one output variables not 0 using Mamdani operator (AND). The rule is as follows:

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Rule 13: If Study Hours per Day is Very Low, and Attendance is Excellent, and Test Score is Very Good, then Mathematics Performance is Excellent.

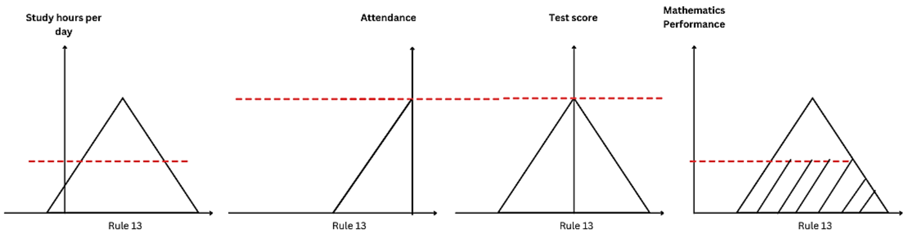

Figure 3: Fuzzy Rule Based for Rule 13

Table 6: Calculation Of Intersection Point In Graph For Excellent Mathematics Performance

Intersection point 1	Intersection point 2	Intersection point 3
$\frac{x-70}{15} = 0.4$ $x = 76$	$\frac{89-x}{4} = 0.4$ $x = 87.4$	$\frac{x-85}{10} = 0.4$ $x = 89$

Table 6 shows all of the calculation of intersection points based on graph of output obtained in Figure 3 and the membership of aggregated fuzzy output for excellent performance as shown below.

$$\mu_{(SH \cap ATT \cap T)} = \begin{cases} \frac{x-70}{15}; & 70 \leq x \leq 76 \\ \frac{89-x}{4}; & 76 \leq x \leq 87.4 \\ \frac{x-85}{10}; & 87.4 \leq x \leq 89 \end{cases}$$

All of the intersection points obtained in Table 6 are inserted to the aggregated fuzzy output in Figure 4. Based on the Figure 4, we can conclude that if the students' study hours is very low, excellent attendance and having very good score in test, they might be end up with excellence final grade that is in the range between 76 and 87.4. The lowest might be 70 and the highest would be 89.

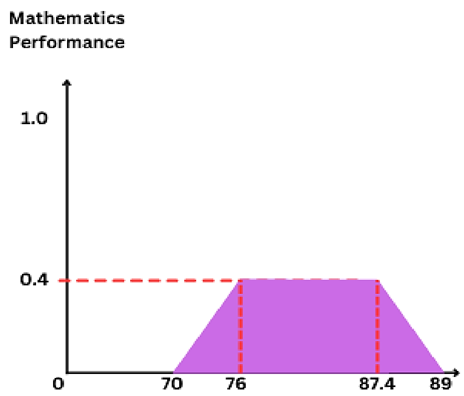

Figure 4: The Aggregated Fuzzy Output

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Stage 4: Defuzzification

Defuzzification is the process in a fuzzy inference system (FIS) where the aggregated fuzzy output, which represents a fuzzy set of possible outcomes, is converted into a single crisp value that predicts the mathematics performance. Below is the calculation performed by using Centre of Gravity (COG) also known as centroid method to convert the aggregate fuzzy set of mathematics performance.

$$x^* = \frac{\int_v^a x \cdot \mu(x)\,dx}{\int_v^a \mu(x)\,dx}$$
$$= \frac{\int_{70}^{76} x\left(\frac{x-70}{15}\right)dx + \int_{76}^{87.4} x\left(\frac{89-x}{4}\right)dx + \int_{87.4}^{89} x\left(\frac{x-85}{10}\right)dx}{\int_{70}^{76}\left(\frac{x-70}{15}\right)dx + \int_{76}^{87.4}\left(\frac{89-x}{4}\right)dx + \int_{87.4}^{89}\left(\frac{x-85}{10}\right)dx}$$
$$= \frac{\frac{444}{5} + 1668.903 + 45.1925}{\frac{6}{5} + 20.805 + 0.512}$$
$$= 80.06819$$

Based on the defuzzification calculation shown above, the mathematics performance score obtained is 80.06819, falls in the excellent category which is in the range between 76 and 87.4. Thus, the model is verified.

Stage 5: Output (Validation)

Since this study aimed to evaluate the validity of the model, validation assesses the performance accuracy and reliability of a model by using the error of prediction formula. The error of prediction refers to the difference between the predicted values generated by the model and the actual observed values in the data. It quantifies how much the predictions deviated from the real outcomes. Lower values of prediction error indicates that the model predictions are closer to the actual values, indicating better performance and accuracy. The error of prediction helps assess the reliability and effectiveness of predictive models in accurately estimating outcomes based on input variables. To determine whether the prediction model iss valid or not, the percentage needed to be below 10%. This error is typically calculated using this formula:

$$Prediction\ error\ (\%) = \frac{|Actual\ data - Predicted\ data|}{Actual\ data} \times 100\%$$

In implementing MATLAB fuzzy tools to develop a mathematics performance prediction system, four main editors from the Fuzzy Logic Toolbox are used to construct and illustrate the fuzzy inference system: the **Fuzzy Logic Designer**, **Membership Function Editor**, **Rule Editor**, and **Rule Viewer**.

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Fuzzy Logic Designer.

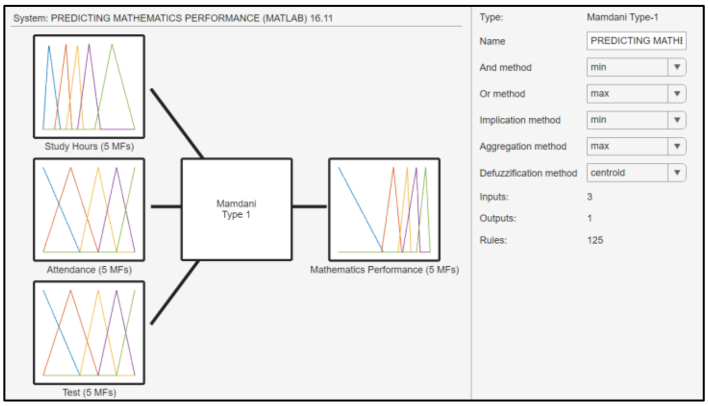

Figure 5: Fuzzy Inference System Interface Input and Output

Figure 5 illustrates a Mamdani system implemented with three input parameters which are study hours per day, student attendance and test scores. The system predicts the mathematics performance of UiTM students based on the specified criteria and rules, with mathematics performance serving as the output parameter.

Membership Function Editor.
This editor is used to define the membership functions for the input and output of each variable. For the input variable, Figure 6 displays the spectrum and range for the input of the study hours per day, based on Table 2 that provides the basis for this input. Figure 7 and Figure 8 display the spectrum and input range for student attendance and for student test score, respectively

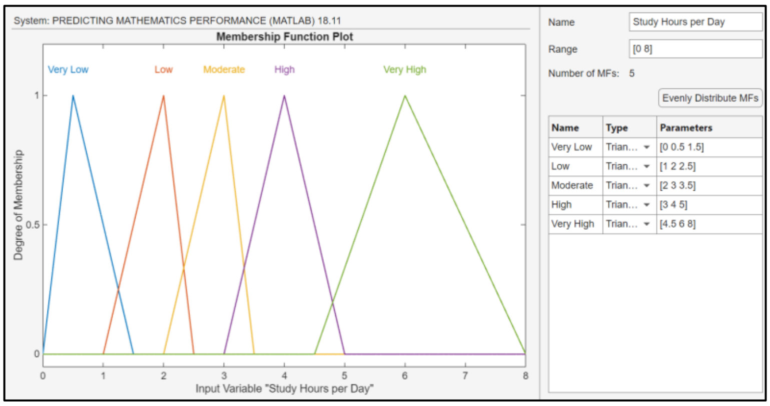

Figure 6: Study Hours Per Day Membership Functions

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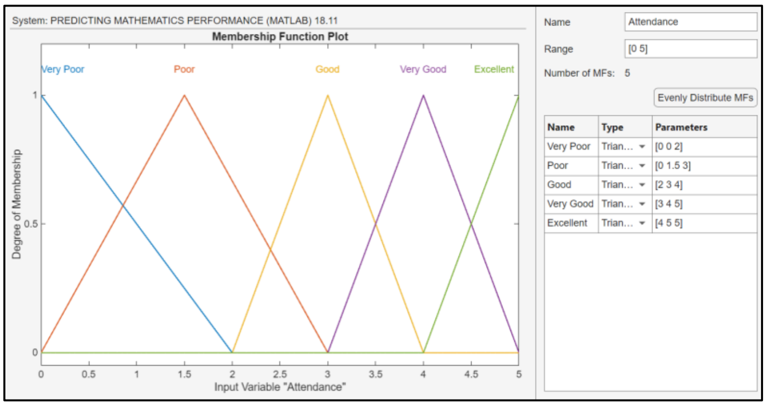

Figure 7: Student Attendance Membership Functions

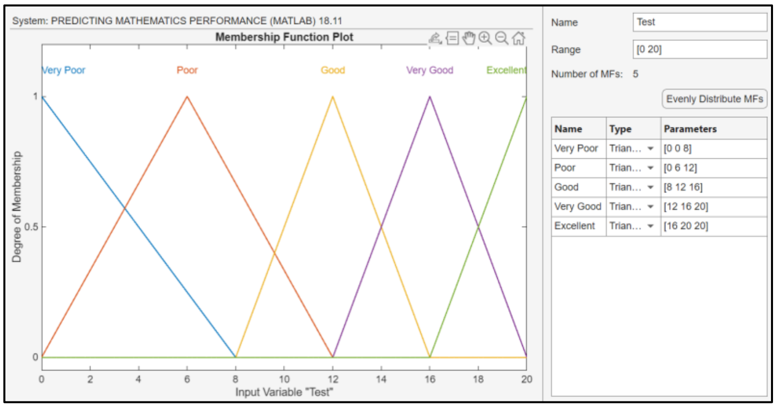

Figure 8: Student Test Score Membership Functions

Figure 9 shows the spectrum and range for the output which was mathematics performance of the students.

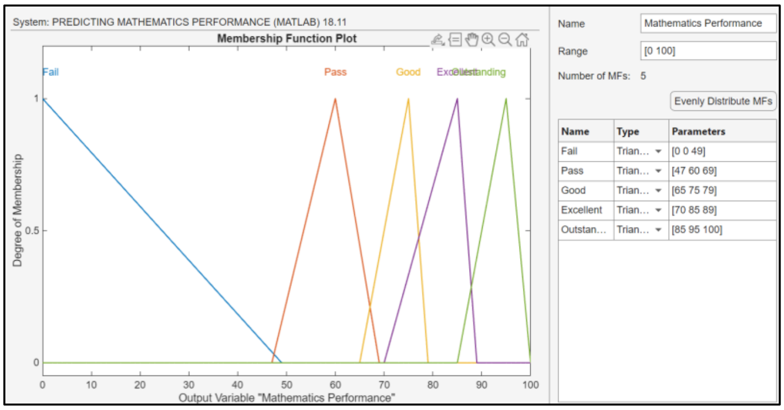

Figure 9: Mathematics Performance of UiTM Students' Membership Functions

Rule Editor

It is used to define all the rules of the fuzzy inference system. The connection for the input variable could be chosen as either 'and' or 'or'.

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	Rule	Weight	Name
1	If Study Hours per Day is Very Low and Attendance is Very Poor and Test is Very Poor then Mathematics Performance is Fail	1	rule1
2	If Study Hours per Day is Very Low and Attendance is Very Poor and Test is Poor then Mathematics Performance is Fail	1	rule2
3	If Study Hours per Day is Very Low and Attendance is Very Poor and Test is Good then Mathematics Performance is Good	1	rule3
4	If Study Hours per Day is Very Low and Attendance is Very Poor and Test is Very Good then Mathematics Performance is Ex...	1	rule4
5	If Study Hours per Day is Very Low and Attendance is Very Poor and Test is Excellent then Mathematics Performance is Exc...	1	rule5
6	If Study Hours per Day is Very Low and Attendance is Poor and Test is Very Poor then Mathematics Performance is Fail	1	rule6
7	If Study Hours per Day is Very Low and Attendance is Good and Test is Very Poor then Mathematics Performance is Fail	1	rule7
8	If Study Hours per Day is Very Low and Attendance is Very Good and Test is Very Poor then Mathematics Performance is Fail	1	rule8
9	If Study Hours per Day is Very Low and Attendance is Excellent and Test is Very Poor then Mathematics Performance is Fail	1	rule9

Figure 10: IF-THEN Rule

Figure 10 shows the first nine rules of IF-THEN Rules for this study. The total of 125 rules are generated in MATLAB.

Rule Viewer

Rule Viewer determine the output by adjusting the value of all inputs as shown in Figure 11. According to the findings, mathematics performance of UiTM students depend on the inputs (study hours per day, student attendance and test score). Suppose the study hours per day fall within the interval of 4, classifying it as high, student attendance scale was 2.5, classifying it as good and test score obtained by student was 10, classifying it as good. In this case, prediction of mathematics performance for this UiTM student would be 64.9%, classifying it as Pass.

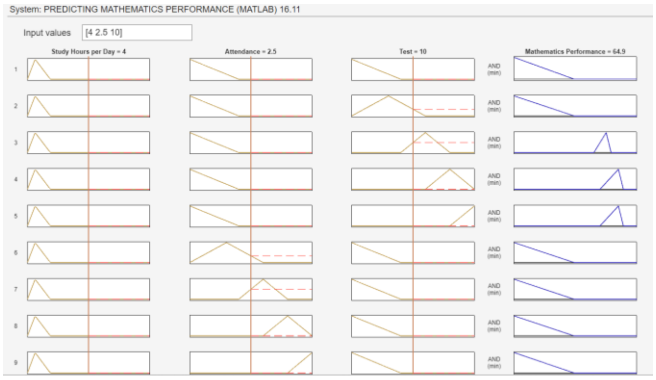

Figure 11: Rule Inference from Fuzzy Logic

Results and Discussions

The outcomes depicted in Table 7 delineate the levels of mathematics performance, including failure, pass, good, excellent and outstanding, contingent upon the values associated with these criteria. The result shows that the fuzzy approach values closely aligned with those obtained using conventional methods for mathematics performance across all samples. These findings of this study were similar to those Petra and Aziz (2021), who found that the fuzzy approach value was close to the results obtained by conventional cumulative grade point average (CGPA) per cohort for all samples. The fuzzy logic approach is clearly helped the process of investigating and analysing mathematics performance.

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Table 7: Raw Data of 45 students

Student	Inputs			Output	Actual Data
	Study hours per day	Attendance	Test score	Mathematics performance	
1	0.8	4.8	2.5	26.9	32
2	1	5	8	58.4	67
3	1.8	5	15	79.5	78
4	0.6	5	6.5	42.4	57
5	0.8	5	4	32.1	42
6	0.8	4.8	14.5	78.6	76
7	1.2	4.8	0.5	25.1	21
8	1.2	4.45	12.5	75.4	70
9	0.8	4.8	6	38.9	40
10	0.2	5	16	80.4	90
11	0.4	4.65	7	44.9	62
12	1	5	9	62	52
13	0.4	5	14.5	78.6	84
14	1.2	5	3.5	32	38
15	1.2	4.8	10.5	64.1	77
16	1	5	9	62	70
17	0.6	4.8	9	62	60
18	0.8	4.8	6	38.9	50
19	0.8	5	10	64.9	60
20	0.4	4.8	8	58.6	53
21	0.4	5	9	62	62
22	1.2	5	12	72.3	81
23	0.4	4.65	13	75.9	70
24	0.8	4.8	8.5	60.3	61
25	1	4.8	11.5	69.1	68
26	0.8	5	9	62	58
27	0.2	5	11	66.5	65
28	0.6	4.8	8.5	60.3	50
29	1	4.65	12.5	74.8	66
30	0.4	5	11.5	69.9	60
31	0.6	4.8	7	45.9	53
32	2	4.8	16	81.2	80
33	0.8	4.8	12.5	74.6	70
34	1.6	5	19	80.9	98
35	0.4	5	11	67.9	66
36	0.8	4.8	15	79.4	76
37	1.2	5	18	80.3	93
38	1.4	5	13.5	77.4	76
39	2	5	16.5	81.3	90
40	1	4.65	14.5	78.2	75
41	1.2	4.8	15.5	78.8	84

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42	1	5	14	77.7	77
43	1.2	5	15.5	78.8	76
44	0.6	5	18.5	80.9	80
45	0.8	4.8	4.5	33.9	36

Evaluating the validity of the model
First, the prediction error for each data was calculated using the formula:

$$\text{Prediction error for each student (\%)} = \frac{|Actual\ data - Predicted\ data|}{Actual\ data} \times 100\%$$

Student	Prediction Error	Student	Prediction Error	Student	Prediction Error
1	15.94	16	11.97	31	12.90
2	12.84	17	3.33	32	1.28
3	1.92	18	22.56	33	6.80
4	25.61	19	9.08	34	17.59
5	23.57	20	11.13	35	2.88
6	3.42	21	0.37	36	4.34
7	19.52	22	10.67	37	13.91
8	7.71	23	8.43	38	1.68
9	2.75	24	0.80	39	10.09
10	10.67	25	1.62	40	4.27
11	27.58	26	7.83	41	6.58
12	19.23	27	2.31	42	0.78
13	6.43	28	20.00	43	4.21
14	15.79	29	12.91	44	1.10
15	16.75	30	16.53	45	7.00

Figure 12: Prediction Error for Each Data of Students

The errors for each data are shown in Figure 12. Then, the average prediction error is calculated by summing all individual errors and dividing by the total number of students as shown below.

$$\text{Average prediction error (\%)} = \frac{\sum Prediction\ error\ for\ each\ student\ (\%)}{Total\ of\ students}$$

$$= \frac{444.67\%}{45} = 9.88\%$$

Since the percentage of average prediction error was 9.88% which was below the threshold of 10%, this value demonstrates that the prediction model reliable even though not as accurate as the findings of Salam et al. (2018), who found that the outcomes of its proposed system equals to the expected results. This study does not include final examination as one of the input because it is expected to be performed before the final examination. Thus, based on the prediction performance, the lecturer will know who are the students will be at risk and take the appropriate action to avoid the students from being underperform. Another comparison, this

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study only uses three factors, while the research by Salam et al. (2018) uses ten factors. As a result, their percentage error was very small, making their model more accurate.

Conclusion and Recommendation

This study highlights the vital role of mathematics in education, particularly within the domains of science. Despite its importance, persistent challenges such as lower student interest, weak foundational knowledge, and negative learning behaviours have contributed to declining mathematics performance among Malaysian students. To address these issues, this study focused on predicting the performance of UiTM Arau, Perlis students enrolled in Calculus I using a fuzzy logic approach. The model incorporated three primary input variables; attendance, study hours, and test scores, to generate predictions about students' academic performance.

The study reinforces the practical value of fuzzy logic in educational settings. By enabling early identification of at-risk students, the model facilitates targeted support, promotes better learning environments, and contributes to the broader goal of academic excellence at UiTM Arau. This research illustrates the wider applicability of predictive models in improving mathematics education across institutions.

To improve prediction accuracy, future studies should consider incorporating additional variables related to mathematics achievement. Research by Acharya et al. (2019) and Salam et al. (2018) highlights other relevant factors such as course load, mental health (e.g., depression levels), and cumulative GPA. Including these parameters could offer a more holistic view of student performance and strengthen the predictive capabilities of the model. Integrating other methodologies such as the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines neural networks with fuzzy logic, might also enhance prediction accuracy. ANFIS has been proven to reduce prediction errors and provide deeper insights into the relationships among academic performance factors (Salam et al., 2018)

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References

Acharya, F. S., Agarwal, G. K., & Panchal, J. G. (2019). Fuzzy Logic Model for evaluating student performance in Engineering Mathematics at Parul University. *Journal of Emerging Technologies and Innovative Research (International Open access Journal).*

Ali, N., Jusoff, K., Ali, S., Mokhtar, N., Syafena, A., & Salamat, A. (2009). The Factors Influencing Students' Performance at Universiti Teknologi MARA Kedah, Malaysia. *Management Science and Engineering*, *3*(4), 81-90.

Ancheta, R. F., Daniel, D., & Ahmad, R. (2021). Effect of class attendance on academic performance. *European Journal of Education Studies*, *8*(9). https://doi.org/10.46827/ejes.v8i9.3887.

Aziz, A., Golap, M. A. U., & Hashem, M. M. A. (2019, May). Student's academic performance evaluation method using fuzzy logic system. In *2019 1st international conference on advances in science, engineering and robotics technology (ICASERT)* (pp. 1-6). IEEE.

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume 7 Issue 25 (June 2025) PP. 342-360
DOI: 10.35631/IJMOE.725024
Balfanz, R., & Byrnes, V. (2012). The importance of being in school: A report on absenteeism in the nation's public schools. *The Education Digest*, *78*(2), 4.

Balfanz, R., Herzog, L., & Mac Iver, D. J. (2007). Preventing Student Disengagement and Keeping Students on the Graduation Path in Urban Middle-Grade Schools: Early Identification and Effective Interventions. *Educational Psychologist, 42*(4), 223-235.

Bhardwaj, A., Tyagi, H., & Dubey, C. (2021, December). Evaluation of Student Performance Using Fuzzy Logic. In *2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)* (pp. 895-897). IEEE.

Black, P., & Wiliam, D. (1998). Assessment and classroom learning. *Assessment in Education: principles, policy & practice, 5*(1), 7-74.

Chen, J., & Lin, T. F. (2008). Class attendance and exam performance: A randomized experiment. *The Journal of Economic Education, 39*(3), 213-227.

Crede, M., Marcus, J., & Kuncel, N. (2008). Study Habits, Skills, and Attitudes: The Third Pillar Supporting Collegiate Academic Performance. *Perspectives on Psychological Science, 3*(6), 425-453.

Epstein, J. L., & Sheldon, S. B. (2002). Present and accounted for: Improving student attendance through family and community involvement. *The Journal of Educational Research, 95*(5), 308-318.

Gottfried, M. A. (2010). Evaluating the relationship between student attendance and achievement in urban elementary and middle schools: An instrumental variables approach. *American Educational Research Journal, 47*(2), 434-465.

Gran, S. S., Ajol, T. A., & Awang Ali, A. N. (2021). Systematic Alternative Fuzzy Logic Evaluator (SAFLE) for student performance evaluation. In *International Exhibition & Symposium on Productivity, Innovation, Knowledge, Education & Design* (pp. 8-11).

Idris, M. F. I. M., Abd Aziz, K. A., & Aminuddin, M. H. (2022). Fuzzy Logic to Evaluate Significant Factors Affecting Students' Academic Performance Through Online Distance Learning. *Journal of Computing Research and Innovation, 7*(1), 57-69.

Ismail, N., & Idris, A. (2021). Fuzzy logic approach in assessing students performance. *Proceedings of Science and Mathematics, 5*, 84–97.

Lieberman, D. A., & Remedios, R. (2007). Do undergraduates' motives for studying change as they progress through their degrees? *British Journal of Educational Psychology, 77*(2), 379–395. https://doi.org/10.1348/000709906x157772

Liu, M. (2022). The Relationship between Students' Study Time and Academic Performance and its Practical Significance. *BCP Education & Psychology*, *7*, 412-415.

Maass, K., Geiger, V., Ariza, M. R., & Goos, M. (2019). The Role of Mathematics in interdisciplinary STEM education. *Zdm*, *51*, 869-884. https://doi.org/10.1007/s11858-019-01100-5

Malaysia Examination Board. (2023, June 8). *Laporan Analisis Keputusan*. http://lp.moe.gov.my/index.php/laporan-analisis-keputusan

Marsh, H. W., & Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering. *British Journal of Educational Psychology, 81*(1), 59–77. https://doi.org/10.1348/000709910x503501

Moon, C. Y., Larke, P. J., & James, M. C. (2022). Examining Mathematics Achievement. *Journal of Ethnic and Cultural Studies*, *9*(1), 226-243.

Nilashi, M., Yadegaridehkordi, E., Ibrahim, O., Samad, S., Ahani, A., & Sanzogni, L. (2019). Analysis of Travellers' Online Reviews in Social Networking Sites Using Fuzzy Logic

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume 7 Issue 25 (June 2025) PP. 342-360
DOI: 10.35631/IJMOE.725024
Approach. *International Journal of Fuzzy Systems, 21*(5), 1367–1378. https://doi.org/10.1007/s40815-019-00630-0

Nor, N. A. M., Azizan, A., Moktar, B., Aziz, A. A., & Nasir, D. S. M. (2021). Modeling Mathematics Performance Between Rural and Urban School Using a Fuzzy Logic Approach. *Journal of Computing Research and Innovation, 6*(1), 79-90.

Peteros, E., Gamboa, A., Etcuban, J. O., Dinauanao, A., Sitoy, R., & Arcadio, R. (2019). Factors affecting mathematics performance of junior high school students. *International Electronic Journal of Mathematics Education, 15*(1), em0556.

Petra, T. Z. H. T., & Aziz, M. J. A. (2021). Analysing student performance in higher education using fuzzy logic evaluation. *Int. J. Sci. Technol. Res*, *10*(1), 322-327.

Salam, S. D., Paul, P., Tabassum, R., Mahmud, I., Ullah, M. A., Rahman, A., & Rahman, R. M. (2018, September). Determination of academic performance and academic consistency by fuzzy logic. In *2018 International Conference on Intelligent Systems (IS)* (pp. 50-57). IEEE.

Saturday, N. R., & Onuodu, F. E. (2019). Evaluation of students' performance using fuzzy logic. *International Journal of Scientific & Engineering Research, 10(*12), 266–272.

Silangan, C. S., Mocsir, R. M., Regner, R. M., & Peteros, E. D. (2023). Predictive analysis on students' academic performance in mathematics. *Global Journal of Educational Studies, 9*(1), 17. https://doi.org/10.5296/gjes.v9i1.21040

Petra, T. Z. H. T., & Aziz, M. J. A. (2021). Analysing student performance in higher education using fuzzy logic evaluation. *Int. J. Sci. Technol. Res*, *10*(1), 322-327.

Zadeh, L. A. (2015). Fuzzy logic—a personal perspective. *Fuzzy sets and systems*, *281*, 4-20.