Griya Journal of Mathematics Education and Application
Volume 5 Nomor 3, September 2025
e-ISSN 2776-124X||p-ISSN 2776-1258
https://mathjournal.unram.ac.id/index.php/Griya/index

Mamdani Fuzzy System for RPL Student Selection: A Case Study from a University in Jember

Devi Rahayu Agustin[1*], Dwi Aldi Hidayatulloh[2], Muhammad Ridho'i[3]

[1,3] *Department of Mathematics Education, STKIP PGRI Lumajang, Lumajang*
[1,2] *Department of Mathematics, FMIPA, State University of Malang, Malang*

devira9626@gmail.com

Diterima: 21-07-2025; Direvisi: 25-09-2025; Dipublikasi: 29-09-2025

Abstract
The student selection process through the Recognition of Prior Learning (RPL) pathway continues to face challenges related to objectivity and transparency, particularly in integrating qualitative and quantitative data from various assessment instruments such as interviews and problem-solving tests. This study aims to develop a decision support system based on the Mamdani-type fuzzy logic to support a fair and standardized RPL student selection process. A quantitative approach was employed through intelligent system modeling, with system implementation carried out using Microsoft Excel by modifying IF-THEN formulas to simulate fuzzy logic principles. The system incorporates two input variables interview scores and problem-solving test scores and one output variable representing admission eligibility, categorized into five levels (A-E). Testing on a sample of ten prospective students showed that the system was able to perform systematic evaluations and generate more objective and consistent admission decisions. The conclusion of this study is that the application of a fuzzy inference system can improve the quality of decision making in the selection of RPL students, as well as support the principles of competency based and fair assessment.

Keywords: Mamdani Fuzzy System, Recognition of Prior Learning (RPL), Fuzzy Logic

Abstrak
Proses seleksi mahasiswa melalui jalur Rekognisi Pembelajaran Lampau (RPL) masih menghadapi permasalahan dalam hal objektivitas dan transparansi, khususnya dalam menggabungkan data kualitatif dan kuantitatif dari berbagai instrumen penilaian seperti wawancara dan tes pemecahan masalah. Penelitian ini bertujuan untuk mengembangkan sistem pendukung keputusan berbasis logika fuzzy tipe Mamdani yang dapat membantu proses seleksi mahasiswa RPL secara adil dan terstandar. Metode yang digunakan adalah pendekatan kuantitatif dengan pemodelan sistem cerdas, serta implementasi sistem dilakukan menggunakan Microsoft Excel melalui modifikasi rumus IF-THEN untuk mensimulasikan prinsip-prinsip logika fuzzy. Sistem ini menggunakan dua variabel input, yaitu skor wawancara dan skor tes pemecahan masalah, serta satu variabel output berupa nilai kelayakan penerimaan yang diklasifikasikan ke dalam lima kategori (A-E). Hasil pengujian pada sepuluh calon mahasiswa menunjukkan bahwa sistem mampu melakukan evaluasi secara sistematis dan menghasilkan keputusan penerimaan yang lebih objektif dan konsisten. Simpulan dari penelitian ini adalah bahwa penerapan sistem inferensi fuzzy dapat meningkatkan kualitas pengambilan keputusan dalam seleksi mahasiswa RPL, serta mendukung prinsip penilaian yang berbasis pada kompetensi dan keadilan.

Kata Kunci: Mamdani Fuzzy System, Rekognisi Pembelajaran Lampau (RPL), Logika Fuzzy

1. INTRODUCTION

Recognition of Prior Learning (RPL) is a mechanism that enables the recognition of prior learning and work experience, whether obtained through formal, non-formal, or informal pathways. Its purpose is to establish professional qualifications or provide access to formal education, particularly in strategic fields of expertise needed by the country (Ali et al., 2024). In Indonesia, this policy has been regulated through Permendikbudristek No. 41 of 2021, which opens up opportunities for work experience and non formal learning to be recognized as academic credits (Kemenristekdikti, 2023b).

Nevertheless, the selection process for students through the RPL pathway presents complex challenges, particularly in integrating qualitative and quantitative data in a manner that is both fair and objective. Assessment instruments such as portfolio evaluations, interviews, and cognitive tests often contain elements of subjectivity, which may compromise the transparency and fairness of decision-making. Accordingly, there is a pressing need for a technology based Decision Support System (DSS) capable of managing data uncertainty and systematically incorporating linguistic assessments. A particularly relevant approach in this context is the Mamdani-type Fuzzy Inference System (Wardoyo & Yuniarti, 2020).

The Mamdani Fuzzy Inference System, developed by Ebrahim Mamdani in 1975, was designed to address uncertainty and decision making complexity through linguistic representations that resemble human reasoning (Zadeh, 1965). This method has been widely applied in various academic contexts, including scholarship selection (Ardiansah dkk., 2024; Elfaladonna & Isa, 2022), mapping of interest areas or fields of expertise (Klau et al., 2023), and determining graduates' employment waiting periods (Aswita Ginting et al., 2023). For instance, the study by Elfaladonna & Isa (2022) demonstrated that the Mamdani method can improve the accuracy of scholarship selection by proportionally integrating both quantitative and qualitative variables. Similarly, Ardiansah dkk., (2024) confirmed the effectiveness of the system in supporting rule-based linguistic decision making.

The Mamdani Fuzzy Inference System has been widely applied in education for decision making such as scholarship selection and academic evaluation. Rustanto (2024) research utilizes the Tsukamoto Fuzzy Logic approach for Decision Support Systems in scholarship recipient selection. The findings of Tsukamoto's fuzzy logic were able to improve the quality of selection to be more fair, inclusive, transparent, and efficient for scholarship recipients. Meanwhile, research by Hidayatulloh et al., (2025) utilized Mamdani's fuzzy logic to evaluate students' readiness to face the Test-Based National Selection at tutoring institutions. The findings of Mamdani's fuzzy logic can be used as an adaptive and contextual evaluation tool in a tutoring environment, thereby supporting more objective and measurable data-based instructional decision-making.

This study aims to develop a Mamdani-type Fuzzy Inference System (as a decision-support tool in the selection process for RPL students at a higher education institution in Jember, Indonesia. The system utilizes two main input variables: the interview score (classified as poor, fair, and good) and the problem-solving test score (classified as low, medium, and high). These inputs are mapped to an output variable representing admission eligibility, categorized into five levels: A, B, C, D, and E. It is anticipated that the system will deliver systematic, transparent, and consistent evaluations, thereby enhancing the fairness and accountability of the selection process through evidence-based decision-making.

2. METHOD

This study adopted a quantitative approach, focusing on the development of a numerical model and data analysis based on fuzzy logic principles. The method used was intelligent system modeling through a Mamdani-type Fuzzy Inference System, aimed at supporting decision-making in the selection of students through the RPL pathway. The Mamdani fuzzy logic method was selected for its high flexibility in processing uncertain and linguistically expressed data. Its primary advantages include its adaptive nature and intuitive rule-based structure, which makes it accessible to stakeholders involved in assessment (Ginting et al., 2023).

The data analysis and calculations were conducted using Microsoft Excel by modifying IF-THEN formulas to simulate fuzzy logic principles. This approach was chosen for its practicality and accessibility, enabling the development of a system capable of delivering objective, transparent, and easily applicable evaluations for the RPLselection process. The following are the stages of the fuzzy logic system as shown in Figure 1.

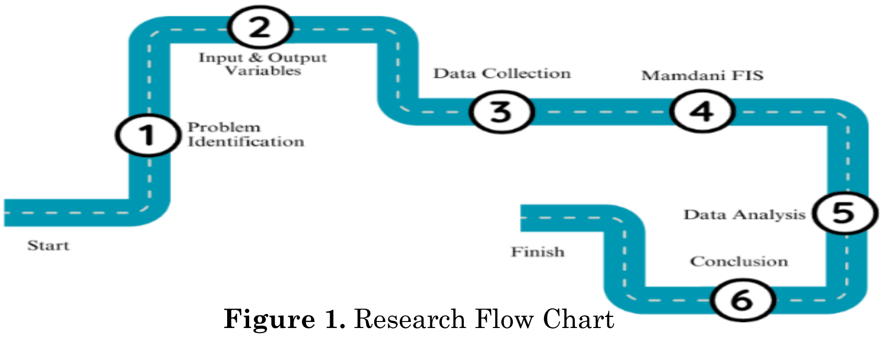


Figure 1. Research Flow Chart

From Figure 1, the stages are described in Table 1 below.

Tabel 1. *Deskripsi Tahapan Fuzzy Logic System*

No.	Levels	Definition
	Start	
1	Problem Identification	The first step involved formulating the main research problem: how to design an objective and standardized selection system for students applying through the Recognition of Prior Learning (RPL) pathway.
2	Input & Output Variables	Selecting interview results and problem-solving test scores as input variables, and eligibility categories (A–E) as the output.
3	Data Collection	Collecting RPL assessment data (portfolios, written tests, interviews) from RPL students
4	Mamdani FIS	The fuzzy inference process consists of the following four main steps: a. Fuzzification: This step converts numerical (crisp) input data into fuzzy values using appropriate membership functions, such as triangular or linear functions. b. Rule base: A set of IF-THEN rules is constructed to represent expert knowledge and serve as the foundation for the decision-making process.

		c. Fuzzy inference: The Mamdani method is applied to process the fuzzy input data and rule base, generating fuzzy output values. d. Defuzzification: The final step transforms the fuzzy output into a crisp value using the centroid method, which calculates the center of gravity of the aggregated output membership function. (Mamdani & Assilian, 1975; Zadeh, 1965).
5	Data Analysis	Performing fuzzy computations using modified Excel logic functions.
6	Conclusion	Interpreting the system output and evaluating its potential for practical implementation in the RPL selection process.
	Finish	

3. RESULTS AND DISCUSSIONS

3.1 Mamdani Fuzzy System Design

3.1.1 Linguistic Variables

This study employed three main linguistic variables in the fuzzy inference system: Interview (W), Problem-Solving Test (TP), and Eligibility Score (NK), with a universe of discourse ranging from 0 to 100 (My et al., 2025; Sumitre & Kurniawan, 2014).

Table 1. Classification of Interview Scores (W)

Classification	Score Range
Poor (K)	$(0 \leq W \leq 50)$
Fair (C)	$(50 < W \leq 65)$
Good (B)	$(65 < W \leq 100)$

Source: (My et al., 2025; Sumitre & Kurniawan, 2014)

This test measures critical and analytical thinking skills. (Pólya & Conway, 2004) problem-solving skills are the ability to make efforts to find solutions to problems encountered. The Fuzzy Set (Linguistic Category) (see Table 2) has a speaker universe ranging from 0 to 100 (Buranda & Bernard, 2019).

Table 2. Classification of Problem-Solving Test Scores (TP)

Classification	Score Range
Low (R)	$(0 \leq TP < 60)$
Medium (S)	$(60 \leq TP < 80)$
High (T)	$(80 \leq TP \leq 100)$

The Feasibility Value is the output of the fuzzy inference process that represents the suitability level of prospective students to be accepted into the RPL pathway. This value is the result of a synthesis of various inputs (interviews and tests). The Fuzzy Set (Linguistic Category) is divided into A, B, C, D, E (see Table 3) with a speaker universe ranging from 0 to 1.

Table 3. Classification of Feasibility Values (NK)

Category	Score range	Admission decision
E	$(0 \leq NK < 0{,}21)$	Not admitted
D	$(0{,}21 \leq NK < 0{,}41)$	Not admitted
C	$(0{,}41 \leq NK < 0{,}61)$	Admitted
B	$(0{,}61 \leq NK < 0{,}81)$	Admitted
A	$(0{,}81 \leq NK \leq 1)$	Admitted

3.1.2 Membership Functions

In a fuzzy system, input and output variables can be classified into different domains using membership functions. For example, the Interview variable is divided into three categories: Poor, Fair, and Good, with a universe of discourse ranging from 0 to 100. Similarly, the Problem-Solving Test variable is grouped into Low, Medium, and High categories, also within the range of 0 to 100. The Eligibility Score is categorized into five levels: A, B, C, D, and E, with a universe of discourse ranging from 0 to 1. Categories A, B, and C indicate that the individual is eligible for admission, while categories D and E indicate that the individual is not eligible. The details of this classification process are further presented in Table 4 bellow.

Table 4. Fuzzy Sets

Function	Variable Name	Linguistic Variables (Fuzzy Sets)		Universe of Discourse
Input	Interview (W)	Poor		[0,100]
		Fair		
		Good		
	Problem-Solving Test (TP)	High		[0,100]
		Medium		
		Low		
Output	Eligibility Score (NK)	A	Admitted	[0,1]
		B	Admitted	
		C	Admitted	
		D	Not Admitted	
		E	Not Admitted	

3.1.3 Fuzzification

Following the definition of linguistic variables and their respective universes of discourse, the subsequent stage involves fuzzification. Fuzzification refers to the process of converting crisp numerical inputs into fuzzy values (Rizvi et al., 2020). This step is essential, as fuzzy systems rely on degrees of membership to linguistic terms rather than on exact numerical values, thereby enabling a more nuanced representation of imprecise or uncertain data.

3.1.3.1 Fuzzification of Interview Scores (W)

Membership function:

$W_K = \mu_K = (0, 0, 40, 50)$

$W_C = \mu_C = (40, 55, 60, 75)$

$W_B = \mu_B = (65,75,100,100)$

Representation of the membership function of the interview in graphical form in Figure 2 below.

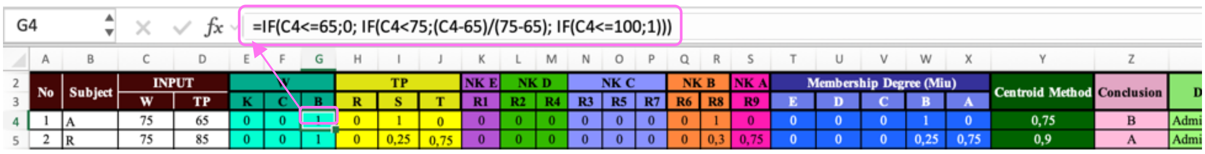
Figure 2. Interview graph

$$\mu_K(x) = \begin{cases} 1 & if\ \ 0 \le x \le 40 \\ \frac{50-x}{(10)} & if\ 40 < x < 50 \\ 0 & if\ x \ge 50 \end{cases}$$

$$\mu_C(x) = \begin{cases} 0 & if\ \ 0 \le x \le 40 \\ \frac{x-40}{15} & if\ 40 < x < 55 \\ 1 & if\ 55 \le x \le 60 \\ \frac{75-x}{15} & if\ 60 < x < 75 \\ 0 & if\ x \ge 75 \end{cases}$$

$$\mu_B(x) = \begin{cases} 0 & if\ \ 0 \le x \le 65 \\ \frac{x-65}{(10)} & if\ 65 < x < 75 \\ 1 & if\ 75 \le x \le 100 \end{cases}$$

The membership degree of the interview can be seen in Figure 3 below.



No	Subject	INPUT		W			TP			NK E	NK D		NK C			NK B		NK A	Membership Degree (Miu)					Centroid Method	Conclusion	D
		W	TP	K	C	B	R	S	T	R1	R2	R4	R3	R5	R7	R6	R8	R9	E	D	C	B	A			
1	A	75	65	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0,75	B	Admi
2	R	75	85	0	0	1	0	0,25	0,75	0	0	0	0	0	0	0	0,3	0,75	0	0	0	0,25	0,75	0,9	A	Admi

Figure 3. Calculation of Interview Degree of Membership

The excel formula for calculating the membership degree of the interview variable is presented in Table 5.

Table 5. Excel Formulas for Membership Degree of Interview variable

Classification	Excel Formula
Poor (K)	$= IF(C4 <= 40; 1;\ IF(C4 < 50; (50 - C4)/(50 - 40);\ IF(C4 >= 50; 0)))$
Fair (C)	$= IF(C4 <= 40; 0;\ IF(C4 < 55; (C4 - 40)/(55 - 40);\ IF(C4 <= 60; 1;\ IF(C4 < 75; (75 - C8)/(75 - 60);\ IF(C4 >= 75; 0)))))$
Good (B)	$= IF(C4 <= 65; 0;\ IF(C4 < 75; (C4 - 65)/(75 - 65);\ IF(C4 <= 100; 1)))$

3.1.3.2 Fuzzification of Problem-Solving Test (TP)

Membership Function:

$TP_R = (0,0,40,60)$

$TP_S = (40,60,70,90)$

$TP_T = (70,90,100,100)$

The representation of the membership function for the Problem-Solving Test scores is illustrated in Figure 4 as follows.

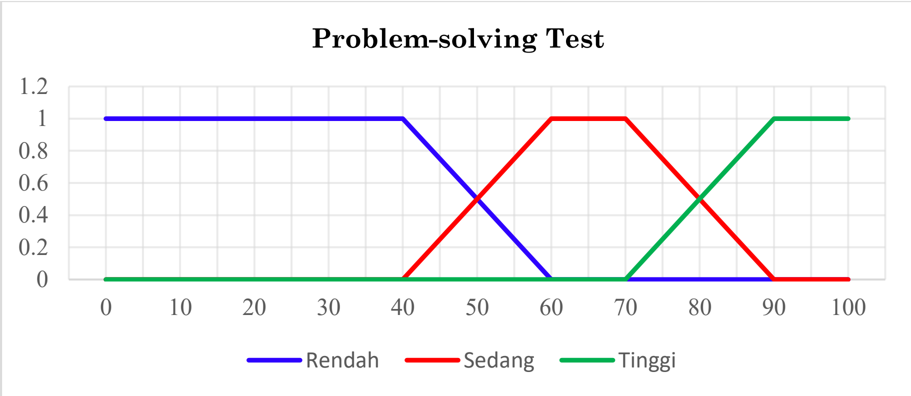


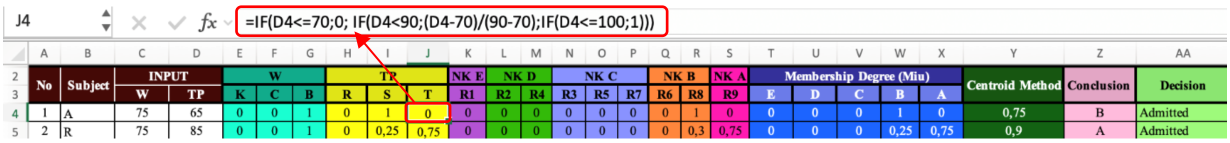
Figure 4. Problem-solving test score graph

$$\mu_{TP\ R}(x) = \begin{cases} 1 & if\ \ 0 \le x < 40 \\ \frac{60-x}{(20)} & if\ 40 \le x < 60 \\ 0 & if\ x \ge 60 \end{cases}$$

$$\mu_{TP\ S}(x) = \begin{cases} 0 & if\ \ 0 \le x < 40 \\ \frac{x-40}{20} & if\ 40 \le x < 60 \\ 1 & if\ 60 \le x < 70 \\ \frac{90-x}{20} & if\ 70 \le x < 90 \\ 0 & if\ x \ge 90 \end{cases}$$

$$\mu_{TP\ T}(x) = \begin{cases} 0 & if\ \ 0 \le x \le 70 \\ \frac{x-70}{20} & if\ 70 < x < 90 \\ 1 & if\ 90 \le x \le 100 \end{cases}$$

The degree of membership of test values can be seen in Figure 5 below.



J4 =IF(D4<=70;0; IF(D4<90;(D4-70)/(90-70);IF(D4<=100;1)))

No	Subject	INPUT		W			TP			NK E	NK D		NK C			NK B		NK A	Membership Degree (Miu)					Centroid Method	Conclusion	Decision
		W	TP	K	C	B	R	S	T	R1	R2	R4	R3	R5	R7	R6	R8	R9	E	D	C	B	A			
1	A	75	65	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0,75	B	Admitted
2	R	75	85	0	0	1	0	0,25	0,75	0	0	0	0	0	0	0	0,3	0,75	0	0	0	0,25	0,75	0,9	A	Admitted

Figure 5. Membership Degree Calculation for the Problem-Solving Test

Meanwhile, the Excel formulas used to compute the membership degree for the Problem-Solving Test are shown in Table 6.

Table 6. Excel Based Formulas for Calculating Membership Degrees of the Problem-Solving Test

Classification	Excel Formula
Low (R)	$= IF(D4 < 40; 1;\ IF(D4 < 60; ((60 - D4)/(60 - 40));\ IF(D4 >= 60; 0)))$
Medium (S)	$= IF(D4 < 40; 0;\ IF(D4 < 60; (D4 - 40)/(60 - 40);\ IF(D4 < 70; 1;\ IF(D4 < 90; (90 - D4)/(90 - 70);\ IF(D4 >= 90; 0)))))$
High (T)	$= IF(D4 <= 70; 0;\ IF(D4 < 90; (D4 - 70)/(90 - 70); IF(D4 <= 100; 1)))$

3.1.3.3 Fuzzyfication of RPL Student Admission Decisions (NK)

Membership Function:

$\mu_E = (0,0,0.2, ,0.3)$

$\mu_D = (0.2, 0.3, 0.4, 0.5)$

$\mu_C = (0.4, 0.5, 0.6, 0.7)$

$\mu_B = (60,70,80,90)$

$\mu_A = (80,90,100,100)$

Figure 6 illustrates the membership function representation of the Eligibility Score for RPL student admission.

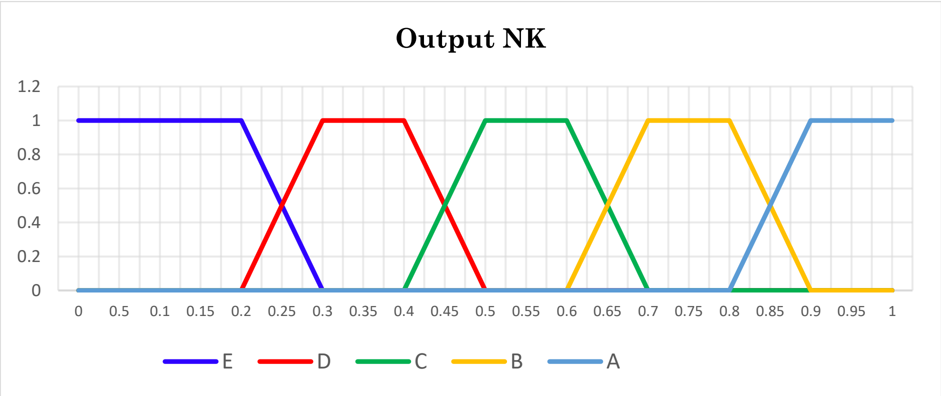


Figure 6. Graph of RPL Student Acceptance Eligibility Scores

$$\mu_E(x) = \begin{cases} 1 & if\ \ 0 \le x \le 0{,}2 \\ \frac{0{,}3-x}{0{,}3-0{,}2)} & if\ 0{,}2 < x < 0{,}3 \\ 0 & if\ x \ge 0{,}3 \end{cases}$$

$$\mu_D(x) = \begin{cases} 0 & if\ \ 0 \le x \le 0{,}2 \\ \frac{x-0{,}2}{(0{,}3-0{,}2)} & if\ 0{,}2 < x < 0{,}3 \\ 1 & if\ 0{,}3 \le x \le 0{,}4 \\ \frac{0{,}5-x}{(0{,}5-0{,}4)} & if\ \ 0{,}4 < x < 0{,}5 \\ 0 & jika\ 0{,}5 \le x \le 1 \end{cases}$$

$$\mu_C(x) = \begin{cases} 0 & if\ \ 0 \le x \le 0{,}4 \\ \frac{x-0{,}4}{(0{,}5-0{,}4)} & if\ 0{,}4 < x < 0{,}5 \\ 1 & if\ 0{,}5 \le x \le 0{,}6 \\ \frac{0{,}7-x}{(0{,}7-0{,}6)} & if\ 0{,}6 < x < 0{,}7 \\ 0 & if\ x \ge 0{,}7 \end{cases}$$

$$\mu_B(x) = \begin{cases} 0 & if\ \ 0 \le x \le 0{,}6 \\ \frac{x-0{,}6}{(0{,}7-0{,}6)} & if\ 0{,}6 < x < 0{,}7 \\ 1 & if\ 0{,}7 \le x \le 0{,}8 \\ \frac{0{,}9-x}{(0{,}9-0{,}8)} & if\ 0{,}8 < x < 0{,}9 \\ 0 & if\ x \ge 0{,}9 \end{cases}$$

$$\mu_A(x) = \begin{cases} 0 & if\ \ 0 \le x \le 0{,}8 \\ \frac{x-0{,}8}{(0{,}9-0{,}8)} & if\ 0{,}8 < x < 0{,}9 \\ 1 & if\ 0{,}9 \le x \le 1 \end{cases}$$

3.1.4 Rule Base

The rule base forms the core of the fuzzy logic decision-making system, linking input and output variables through IF-THEN statements. Each input variable, such as interview performance (poor, fair, and good) and problem-solving test scores (low, medium, high), is categorized linguistically. The system output is the eligibility score for RPL student admission, which is classified into two categories: admitted and not admitted.

Table 7. Rule Base for RPL Student Admission Eligibility

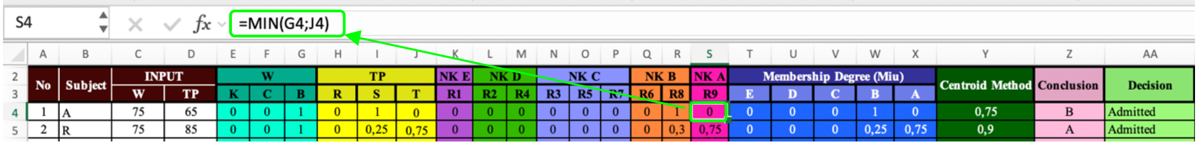
No	IF	Input		Rule	Then	Output (NK)	Decision	Symbol (R_i)
		(W)	(TP)					
1	if	K	R		Then	E	Not Admitted	R1
2	If	K	S	K-R	Then	D	Not Admitted	R2
3	If	K	T	K-S	Then	C	Admitted	R3
4	If	C	R	K-T	Then	D	Not Admitted	R4
5	If	C	S	C-R	Then	C	Admitted	R5
6	If	C	T	C-S	Then	B	Admitted	R6
7	If	B	R	C-T	Then	C	Admitted	R7
8	If	B	S	B-R	Then	B	Admitted	R8
9	If	B	T	B-S	Then	A	Admitted	R9

3.1.5 Inference

After the fuzzification and rule base formulation stages, the next step involves the fuzzy inference process. The inference engine is responsible for applying the predefined rules to the fuzzy inputs in order to generate fuzzy outputs. These rules evaluate linguistic input values and map them to corresponding fuzzy sets. The resulting fuzzy outputs then require a defuzzification process to be converted into crisp values. Each inference rule consists of an IF–THEN statement that connects input and output linguistic variables. The rule evaluation commonly uses the minimum operator, expressed as:

$$\mu A \cap B(x) = \min\left[\mu A(x), \mu B(x)\right]$$

which can also be implemented using spreadsheet functions in Microsoft Excel, as shown in Figure 7.

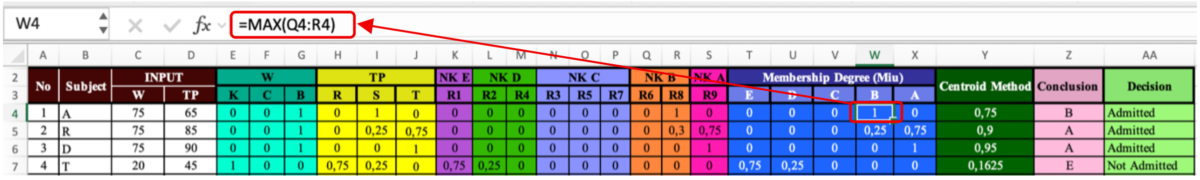


S4 =MIN(G4;J4)

No	Subject	INPUT		W			TP			NK E	NK D		NK C			NK B		NK A	Membership Degree (Miu)					Centroid Method	Conclusion	Decision
		W	TP	K	C	B	R	S	T	R1	R2	R4	R3	R5	R7	R6	R8	R9	E	D	C	B	A			
1	A	75	65	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0,75	B	Admitted
2	R	75	85	0	0	1	0	0,25	0,75	0	0	0	0	0	0	0	0,3	0,75	0	0	0	0,25	0,75	0,9	A	Admitted

Figure 7. Excel Formulas Based on the Minimum Rule for Fuzzy Inference

Subsequently, the aggregation process is carried out using the maximum operator to select the highest membership value from the resulting fuzzy outputs. The result is a new fuzzy set for the output variable, Eligibility Score (NK), with membership degrees corresponding to A, B, C, D, and E. These values represent the potential admission status of candidates (admitted or not admitted) in fuzzy form (see Figure 8).



W4 =MAX(Q4:R4)

No	Subject	INPUT		W			TP			NK E	NK D		NK C			NK B		NK A	Membership Degree (Miu)					Centroid Method	Conclusion	Decision
		W	TP	K	C	B	R	S	T	R1	R2	R4	R3	R5	R7	R6	R8	R9	E	D	C	B	A			
1	A	75	65	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0,75	B	Admitted
2	R	75	85	0	0	1	0	0,25	0,75	0	0	0	0	0	0	0	0,3	0,75	0	0	0	0,25	0,75	0,9	A	Admitted
3	D	75	90	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0,95	A	Admitted
4	T	20	45	1	0	0	0,75	0,25	0	0,75	0,25	0	0	0	0	0	0	0	0,75	0,25	0	0	0	0,1625	E	Not Admitted

Figure 8. Excel Formulas Based on Max Rule Aggregation

3.1.6 Defuzzification

Defuzzification is the process of converting fuzzy outputs into crisp values for decision-making purposes. In this study, the output variable Eligibility Score (NK) comprises five linguistic categories: A, B, C, D, and E. Categories A through C indicate "admitted," whereas D and E indicate "not admitted." The inference result is a composite fuzzy area, determined by the contribution of each rule. To obtain the final crisp value, the centroid method is employed, which calculates the center of gravity of the aggregated fuzzy area using the discrete formula:

$$z = \frac{\sum_{j=1}^{n} z_j \mu_c(z_j)}{\mu_c(z_j)}$$

(Rizvi dkk., 2020; Zadeh, 1965).

Alternatively, this can be implemented in Excel using the formula $= (\mathrm{T4} * 0{,}1) + (\mathrm{U4} * 0{,}35) + (\mathrm{V4} * 0{,}55) + (\mathrm{W4} * 0{,}75) + (\mathrm{X4} * 0{,}95) / (\mathrm{T4} + \mathrm{U4} + \mathrm{V4} + \mathrm{W4} + \mathrm{X4})$.

The resulting crisp output values are visualized in the following figure 9.

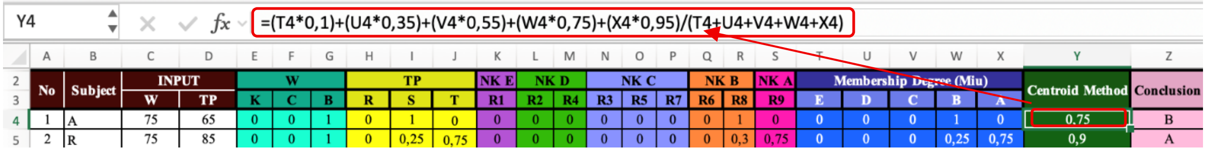


Figure 9. Centroid Method

In the context of this study, the results of defuzzification using the centroid method will determine the decision on whether a prospective student is accepted or rejected as a student, based on the final score obtained. The defuzzification results are then classified into five categories: A, B, C, D, and E. This classification aims to facilitate the interpretation of evaluation results and serve as a basis for further decision-making. The formula in Excel is as follows = IF(Y4 >= 0,81; "A"; IF(Y4 >= 0,61; "B"; IF(Y4 >= 0,41; "C"; IF(Y4 >= 0,21; "D"; IF(Y4 >= 0; "E"))))).

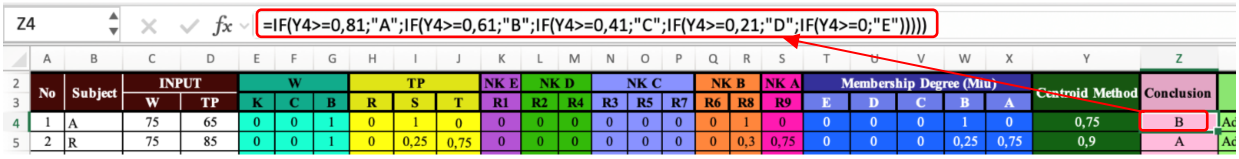


Figure 10. Conclusion on the acceptance value of RPL students

Based on the predefined eligibility categories, a final decision is made regarding the admission status of each applicant. Candidates whose scores fall within categories A to C are classified as admitted through the RPL pathway, while those with scores in categories D and E are considered not admitted (see Table 3). This decision is made objectively, based on data processing using the fuzzy logic system. The corresponding Excel formula is as follows: = IF(Z4A; "Admitted"; IF(Z4 = "B"; "Admitted"; IF(Z4 = "C"; "Admitted"; IF(Z4 = "D"; "Not Admitted"; IF(Z8 = "E"; "Not Admitted"))))).

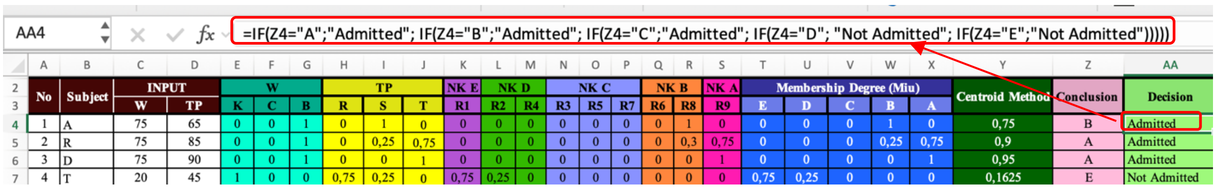


Figure 11. RPL Student Admission Decision

3.2 Implementation (case study of RPL student admission)

This study utilized a sample of 10 prospective students who participated in the RPL admission selection process. The data were analyzed to determine the final selection outcome for each candidate. The decision-making process began by inputting two key variables Interview (W) and Problem-Solving Test (TP), which served as the basis for determining the final admission decision.

Table 8. RPL Admission Results

Subject	W	TP	Degree of membership					Centroid Method	Conclusion	Decision
			A	B	C	D	E			
A	75	65	0	0	0	1	0	0,75	B	Admitted
R	75	85	0	0	0	0,25	0,75	0,94	A	Admitted
D	75	90	0	0	0	0	1	1	A	Admitted
T	20	45	0,75	0,25	0	0	0	0,06	E	Not Admitted
M	30	45	0,75	0,25	0	0	0	0,06	E	Not Admitted
O	80	90	0	0	0	0	1	0,95	A	Admitted
P	50	70	0	0	0,67	0	0	0,36666667	D	Not Admitted
S	75	50	0	0	0,5	0,5	0	0,65	B	Admitted
F	50	80	0	0	0,5	0,5	0	0,65	B	Admitted
V	50	60	0	0	0,67	0	0	0,36666667	D	Not Admitted

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
2	No	Nama	INPUT		W (wawancara)			TP (Tes Kemampuan)			NK E	NK D		NK C			NK B		NK A	Derajat Keanggotaan (Miu)					Metode Centroid	Kesimpulan	Keputusan
3			W	TP	K	C	B	R	S	T	R1	R2	R4	R3	R5	R7	R6	R8	R9	E	D	C	B	A			
4	1	A	75	65	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0,75	B	Diakui
5	2	R	75	85	0	0	1	0	0,25	0,75	0	0	0	0	0	0	0	0,25	0,75	0	0	0	0,25	0,75	0,9	A	Diakui
6	3	D	75	90	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0,95	A	Diakui
7	4	T	20	45	1	0	0	0,75	0,25	0	0,75	0,25	0	0	0	0	0	0	0	0,75	0,25	0	0	0	0,1625	E	Tidak diakui
8	5	M	30	45	1	0	0	0,75	0,25	0	0,75	0,25	0	0	0	0	0	0	0	0,75	0,25	0	0	0	0,1625	E	Tidak diakui
9	6	O	80	90	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0,95	A	Diakui
10	7	P	50	70	0	0,67	0	0	1	0	0	0	0	0	0,67	0	0	0	0	0	0	0,67	0	0	0,366666667	D	Tidak diakui
11	8	S	75	50	0	0	1	0,5	0,5	0	0	0	0	0	0	0,5	0	0,5	0	0	0	0,5	0,5	0	0,65	B	Diakui
12	9	F	50	80	0	0,67	0	0	0,5	0,5	0	0	0	0	0,5	0	0,5	0	0	0	0	0,5	0,5	0	0,65	B	Diakui
13	10	V	50	60	0	0,67	0	0	1	0	0	0	0	0	0,67	0	0	0	0	0	0	0,67	0	0	0,366666667	D	Tidak diakui

Figure 12. Excell Results of RPL Student Admissions

4. CONCLUSION

The implementation of the fuzzy theory in this study is expected to assist decision-making in the selection process for students applying through the RPL (Recognition of Prior Learning) pathway. The system incorporates two primary inputs interview performance and problem solving test results which are processed using fuzzy logic rules to generate an output in the form of an admission eligibility score. This approach enables a more objective, flexible, and competency based evaluation, particularly suited for non-traditional pathways like RPL. Moreover, the system holds potential to enhance the transparency and efficiency of the selection process.

5. RECOMMENDATION

Further research is recommended to expand input variables, such as work experience and portfolios, to improve assessment accuracy. System integration with campus digital platforms is also necessary to support efficient implementation. In addition, user satisfaction evaluations are important to comprehensively measure the effectiveness and acceptance of the system.

6. REFERENCE

Ali, M., Halik, W., Ramli, U., Banggu, M., Salmawati, Rais, L., Basri, L., Wahid, B., Hidaya, N., Sangadji, I. M., & Purnomo, A. (2024). Sosialisasi Sistem Pendidikan Rekognisi

Pembelajaran Lampau (RPL) di Pemerintah Kota Sorong. *Abdimas: Papua Journal of Community Service*, *6*(1), 49–57. https://doi.org/10.33506/pjcs.v6i1.3128

Ardiansah, Y., Luchia, N. T., Hastari, D., Rifat, T. M. F., Rachfaizi, R., Putri, N. A., & Ginting, E. S. (2024). Application of The Fuzzy Mamdani Method in Determining KIP-Kuliah Recipients for New Students. *Public Research Journal of Engineering, Data Technology and Computer Science*, *2*(1), 11–17. https://doi.org/10.57152/predatecs.v2i1.1087

Aswita Ginting, R., Febrian, D., Mobo, F. D., & Dehham, S. H. (2023). Decision Support System in Determining the Job Waiting Period for Graduates of Unimed Using the Mamdani Method of Fuzzy Logic. *Numerical: Jurnal Matematika Dan Pendidikan Matematika*, *7*(2), 275–286. https://doi.org/10.25217/numerical.v7i2.3105

Buranda, M. S., & Bernard, M. (2019). Analisis Kemampuan Pemecahan Masalah Matematik Materi Lingkaran Siswa Smp Berdasarkan Gender. *JPMI (Jurnal Pembelajaran Matematika Inovatif)*, *2*(1), 33. https://doi.org/10.22460/jpmi.v2i1.p33-40

Elfaladonna, F., & Isa, I. G. T. (2022). UJI EFEKTIFITAS METODE FUZZY LOGIC MAMDANI PADA PENERIMAAN BEASISWA BANTUAN MENGGUNAKAN MATLAB. *SINTECH (Science and Information Technology) Journal*, *5*(1), 75–86. https://doi.org/10.31598/sintechjournal.v5i1.1043

Hidayatulloh, D. A., Walida, S. E., & Soemantri, S. (2025). Fuzzy Logic in Education: Profile of Students' Readiness to Prepare for Test-Based National Selection in Study Centers. *Journal of Research in Mathematics Trends and Technology*, *7*(2), 049–059.

Kemenristekdikti. (2023b). *Rekognisi Pembelajaran Lampau*. https://dikti.kemdikbud.go.id/wp-content/uploads/2023/04/Panduan-Banpem-Pelaksanaan-RPL-Tipe-A-2023-1-1.pdf

Klau, D. Y., Tursina, T., & Novriando, H. (2023). Implementasi Metode Fuzzy Inference System (FIS) Mamdani dalam Pemilihan Bidang Keahlian Mahasiswa. *Jurnal Impresi Indonesia*, *2*(4), 372–383. https://doi.org/10.58344/jii.v2i4.2389

Mamdani, E. H., & Assilian, S. (1975). An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller. *International Journal of Man-Machine Studies*, *7*(1), 1–13. https://doi.org/10.1016/S0020-7373(75)80002-2

My, N., Ardiansyah, M., & Sarbani, A. A. (2025). Meningkatkan Keaktifan Siswa Melalui Model Project Based Learning dengan Pendekatan TPACK. *Pinisi Journal PGSD*, *5*(1), 62–68. https://www.researchgate.net/publication/390049385_Meningkatkan_Keaktifan_Siswa_Melalui_Model_Project_Based_Learning_dengan_Pendekatan_TPACK

Pólya, G., & Conway, J. H. (2004). *How to solve it: A new aspect of mathematical method* (Expanded Princeton Science Library ed). Princeton University Press.

Rizvi, S., Mitchell, J., Razaque, A., Rizvi, M. R., & Williams, I. (2020). A fuzzy inference system (FIS) to evaluate the security readiness of cloud service providers. *Journal of Cloud Computing*, *9*(1), 42. https://doi.org/10.1186/s13677-020-00192-9

Rustanto, H. S. (2024). *Enhancing Scholarship Recipient Selection: A Fuzzy Logic- Based Decision Support System Utilizing the Tsukamoto Method*. *18*(2).

Sumitre, M., & Kurniawan, R. (2014). Rancang Bangun Sistem Pendukung Keputusan Seleksi Penerimaan Tenaga Pengajar Dengan Metode Fuzzy Inference System (Fis) Mamdani. *Jurnal Informatika*, *14*(1), 61–71.

Wardoyo, R., & Yuniarti, W. D. (2020). Analysis of Fuzzy Logic Modification for Student Assessment in e-Learning. *IJID (International Journal on Informatics for Development)*, *9*(1), 29. https://doi.org/10.14421/ijid.2020.09105

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3). https://doi.org/10.1016/S0019-9958(65)90241-X

Zadeh, L. H. (1965). *Fuzzy sets* (Vol. 8, pp. 338–353). https://www.sciencedirect.com/science/article/pii/S001999586590241X