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Redefining Academic Recruitment Using Fuzzy Tahani Logic: A Multi-Criteria Model for Calculus Teaching Assistants' Selection

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Abstract

This study introduces a novel application of the Tahani fuzzy logic method in academic recruitment by developing a multi-criteria decision support model for selecting Calculus teaching assistants. While fuzzy logic has been widely used in industrial and engineering decision systems, its use in academic recruitment, particularly for teaching assistant selection, remains largely unexplored. The proposed model evaluates candidates across four key topics in Calculus, including definite integrals and areas between curves. Participants' scores were fuzzified into three linguistic categories: poor, fair, and good, using triangular membership functions, and processed through a rule-based inference system. The final recommendation scores were obtained by defuzzifying the fuzzy outputs. Candidates with a final score of at least 0.5 were classified as eligible. The results demonstrate that the proposed fuzzy Tahani model provides a transparent and objective framework for handling uncertainties in academic assessments, with eight participants meeting the selection threshold. This study expands the application of fuzzy decision systems to the academic domain, offering a systematic and data-driven approach for teaching assistant recruitment.

Keywords: recruitment, fuzzy logic, tahani, multi criteria

1. Introduction

The recruitment and selection of teaching assistants in higher education institutions play a critical role in maintaining the quality of education. This process typically involves multiple evaluation criteria, including academic performance, teaching capability, and the results of specific assessments. Therefore, a well-structured and objective selection mechanism is essential to identify the most qualified candidates. Several previous studies have indicated that conventional selection processes still face challenges in terms of efficiency and accuracy. As a result, there has been a growing reliance on intelligent multi-criteria decision-making systems, such as those based on fuzzy logic principles, to enhance objectivity and decision quality (Alhasan et al., 2023)**,** (Liu, 2014)**,** (Rao, 2013)**,** (Verina et al., 2018)**,** (Sitohang et al., 2023).

In addition to efficiency, objectivity and transparency are critical components of academic selection processes. Numerous studies in the field of education have emphasized that admission and recruitment decisions are often influenced by subjective judgments. Several recent works have reported that the recruitment of prospective educators is frequently hindered by biases and subjective decision-making, which may compromise the fairness and integrity of the process (Moratti, 2020)**,** (Abramo et al., 2015)**,** (Sadiq et al., 2019). These findings highlight the urgent need for more objective, transparent, and equitable mechanisms to support candidate evaluation. A fair and unbiased selection process is especially vital to ensure that recipients of academic appointments or support are chosen based on demonstrated merit, rather than external factors unrelated to the established evaluation criteria. In multi-criteria decision-making scenarios, the selection process becomes increasingly complex. The existence of multiple assessment dimensions and the involvement of various stakeholders often complicate the manual ranking of candidates, thereby reinforcing the need for intelligent decision support systems.

Previous studies have emphasized the need to implement decision support systems (DSS) based on multi-criteria methods to address these challenges. A DSS allows multiple evaluation criteria to be modeled and processed simultaneously, thereby assisting decision-makers in comparing alternatives more objectively. In today’s information-driven era, the use of DSS in the recruitment of teaching assistants has been widely proposed to improve the speed, accuracy, and traceability of the selection process. Fuzzy set theory has emerged as a particularly relevant approach for addressing uncertainty in multi-criteria decision-making problems. In Multi-Criteria Decision-Making (MCDM) problems, the data associated with evaluation criteria are often uncertain, incomplete, or imprecise. To address this uncertainty, fuzzy logic provides an effective and flexible approach for modeling and processing ambiguous information (Faizi et al., 2018)**,** (Pelissari et al., 2021). By utilizing fuzzy logic, linguistic or range-based values (e.g., "high," "medium," "low") can be incorporated into the decision-making process, allowing for a more flexible model that accommodates variations in evaluation. This approach is particularly well-suited for academic selection contexts, which often involve subjective judgments and a wide range of assessment criteria. The type of fuzzy logic that applies this principle is **Tahani’s fuzzy logic**, in which the decision support system is based on actual data and incorporates linguistic evaluations of criteria. This method allows for the integration of real-world data with qualitative assessments, making it particularly suitable for selection processes involving both measurable and subjective indicators.

Although fuzzy-based decision models have been applied in various fields such as learning analytics, tourism management, and business optimization (Nurlayli et al., 2017)**,** (Gerhana et al., 2018)**,** (Alqodri et al., 2021), there remains a lack of studies exploring their application in academic recruitment, particularly in the selection of teaching assistants (TAs). Unlike most existing domains, TA recruitment involves assessing not only numerical academic indicators, but also linguistic judgments related to teaching competence and conceptual understanding. This study therefore fills a research gap by introducing the Tahani fuzzy logic model as a novel multi-criteria decision support framework specifically designed for academic recruitment. The model evaluates student competencies across four calculus-based criteria: Derivative of Composite Functions, Derivative of Integral Functions, Definite Integrals for the Area under a Curve, and Definite Integrals for the Area between Two Curves. By doing so, this research demonstrates the feasibility and effectiveness of extending the Tahani fuzzy model beyond its traditional applications into the educational recruitment domain, contributing both methodologically and contextually to fuzzy logic-based decision systems.

A total of 43 students participated in the selection process of which 23 were ultimately chosen as teaching assistants. The relatively large number of candidates, combined with the need for a fair and transparent selection process, underscores the importance of implementing a multi-criteria decision support system in this context.

2. Methods

This study employs a quantitative approach with a descriptive method to design and implement a decision support system based on the Tahani fuzzy logic for the selection of teaching assistants in a Calculus course. The choice of this method is driven by the need to handle multi-criteria evaluations that are linguistic and subjective in nature, making the fuzzy logic approach particularly suitable. Four criteria are considered as input variables in this study, namely: *Derivative of Composite Functions*, *Derivative of Integral Functions*, *Definite Integrals for the Area under a Curve*, and *Definite Integrals for the Area between Two Curves*. Meanwhile, the linguistic variables used to classify the abilities of the prospective teaching assistants participating in the selection process are $\boldsymbol{\alpha}$*: good*, *fair*, and *poor*.

The test was administered in written form, and the scores obtained in each assessed mathematics domain were converted into fuzzy values. The test was conducted in written form, and the scores obtained in each assessed area of mathematics were converted into fuzzy values based on predefined reference standards to determine fuzzy membership. This process is also known as fuzzification (Li, 2025), (Lima et al., 2025). The membership function in this study following the function below:

$$\boldsymbol{\mu}\ \text{Poor}\ [\boldsymbol{\alpha}] = \begin{cases} \mathbf{1} \ ; & \boldsymbol{\alpha} \le \boldsymbol{p} \\ \dfrac{\boldsymbol{q}-\boldsymbol{\alpha}}{\boldsymbol{q}-\boldsymbol{p}}; & \boldsymbol{p} < \boldsymbol{\alpha} < \boldsymbol{q} \\ \mathbf{0} \ ; & \boldsymbol{\alpha} \ge \boldsymbol{q} \end{cases} \tag{1}$$

$$\boldsymbol{\mu}\text{ Fair }[\boldsymbol{\alpha}] = \begin{cases} \mathbf{0}\ ; & \boldsymbol{\alpha} \le \boldsymbol{p} \\ \dfrac{\boldsymbol{\alpha}-\boldsymbol{p}}{\boldsymbol{q}-\boldsymbol{p}}; & \boldsymbol{p} < \boldsymbol{\alpha} < \boldsymbol{q} \\ \dfrac{\boldsymbol{r}-\boldsymbol{\alpha}}{\boldsymbol{r}-\boldsymbol{q}}; & \boldsymbol{q} < \boldsymbol{\alpha} < \boldsymbol{r} \\ \mathbf{0}, & \boldsymbol{\alpha} \ge \boldsymbol{r} \end{cases} \tag{2}$$

$$\boldsymbol{\mu}\text{ Good }[\boldsymbol{\alpha}] = \begin{cases} \mathbf{0}\ ; & \boldsymbol{\alpha} \le \boldsymbol{q} \\ \dfrac{\boldsymbol{\alpha}-\boldsymbol{q}}{\boldsymbol{r}-\boldsymbol{q}}; & \boldsymbol{q} < \boldsymbol{\alpha} < \boldsymbol{r} \\ \mathbf{1}\ ; & \boldsymbol{\alpha} \ge \boldsymbol{r} \end{cases} \tag{3}$$

Continuing with the calculation process, the decision-making model is based on the computation of a recommendation score, which follows the SQL-style formula as shown below:

$$\frac{\boldsymbol{Good\_DFC} + \boldsymbol{Good\_DIF} + \boldsymbol{Good\_DIAC} + \boldsymbol{Good\_DIATC}}{\mathbf{4}} = \boldsymbol{Final\ score\ recommendation} \tag{4}$$

The above steps represent the general stages of applying the Tahani fuzzy logic, which include the fuzzification stage, the determination of criteria/linguistic variables, and the formulation of decision recommendations (Abdullah et al., 2018)**,** (Rizaldi et al., 2021). The data processing of the selection score results was carried out using Microsoft Excel software, and each test topic was assigned the following weighting in the evaluation. The use of Microsoft Excel in this study was intended for proof-of-concept demonstration. Future implementations using MATLAB or Python fuzzy libraries are planned to strengthen system performance and generalizability.

Table 1.
Standard Assessment Reference

Topics	Max. Point	Max. Weight
Derivative of Composite Functions (DFC)	8	25
Derivative of Integral Functions (DIF)	6	15
Definite Integrals for the Area under a Curve (DIAC)	10	30
Definite Integrals for the Area between Two Curves (DIATC)	10	30

In general, the score for each test is obtained using the following equation.

$$Test\ score = \frac{obtained\ score}{Max.Point} \times Max.Weight \tag{5}$$

In this study, the researchers established the inference rule by setting a threshold for the *Final Score Recommendation* in **Equation 4**. Participants with a final score recommendation greater than or equal to 0.5 were classified as having passed the test.

3. Result and Discussion

This section presents how each test item, consisting of four different questions aligned with fundamental calculus topics, was fuzzified using linguistic membership functions. Each participant's score for each question was converted into a fuzzy value based on three linguistic categories: poor, average, and good. This fuzzification process aims to accommodate uncertainty and variability in test results, thereby supporting the fuzzy logic-based decision support system in determining participants' eligibility to become teaching assistants.

3.1 Membership Function

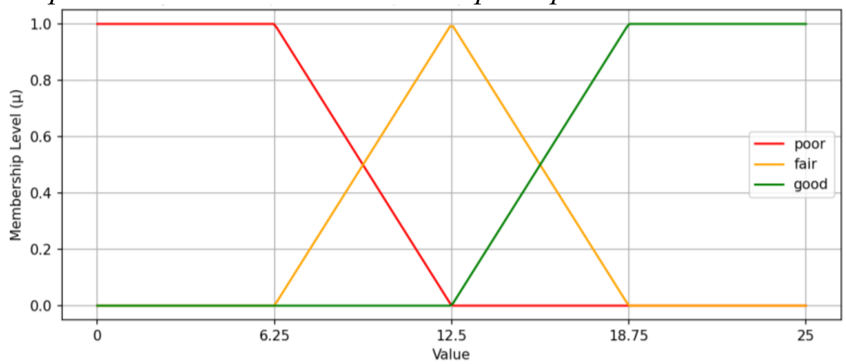
The construction of membership functions plays a critical role in the fuzzification process, which transforms crisp numerical scores into degrees of membership in linguistic categories. For each test topics such as the derivative of composite functions, the derivative of integral functions, definite integrals for the area under a single curve, and definite integrals for the area between two curves three fuzzy linguistic variables are defined: *poor*, *fair*, and *good*. Each of these categories is represented using specific membership functions: a decreasing linear function for *poor*, a symmetric triangular function for *fair*, and an increasing linear function for *good*. These functions are formulated based on the distribution of participants' scores and discretized into appropriate intervals to ensure accurate modeling of performance levels. This approach is consistent with previous research in educational assessment using fuzzy logic, where crisp test scores are fuzzified into linguistic categories such as poor, fair, and good through appropriately defined membership functions (Arslan Namli & Şenkal, 2018)**,** (Doz et al., 2022a)**,** (Doz et al., 2022b).

3.1.1 Membership Function for the Derivative of Composite Functions Test

In the output variable for the composite function derivative skills test, three fuzzy linguistic categories are defined: poor, fair, and good. Each category is represented by a distinct membership function: the "poor" category is modeled using a decreasing linear function, the "fair" category employs a symmetric triangular function, and the "good" category is represented by an increasing linear function.

To visualize the membership functions, the following figure illustrates the fuzzy representation graph generated using Python. The score for this problem has a maximum value of 25 points and based on the actual distribution of the participants' results, the scores range from 0 to 25. These scores are then mapped into fuzzy values by discretizing the score domain into three linguistic segments: *poor* [0; 6,25; 12,5]; *fair* [6,25; 12,5; 18,75]; and *good* [12,5; 18,75; 25].

Figure 1.
Derivative of Composite Functions Test Membership Graph



The membership function formulas for each fuzzy category of the test score variable in the *Derivative of Composite Functions* are defined as follows.

$$\mu_{\text{poor}}(x) = \begin{cases} \mathbf{1}, & x \le 6,25 \\ \frac{12,5-x}{12,5-6,25}, & 6,25 < x < 12,5 \\ \mathbf{0}, & x \ge 12,5 \end{cases} \tag{6}$$

$$\mu_{\text{fair}}(x) = \begin{cases} 0, & x \le 6,25 \\ \frac{x-6,25}{12,5-6,25}, & 6,25 < x < 12,5 \\ \frac{18,5-x}{18,5-12,5}, & 12,5 < x < 18,75 \\ 0, & x \ge 18,75 \end{cases} \tag{7}$$

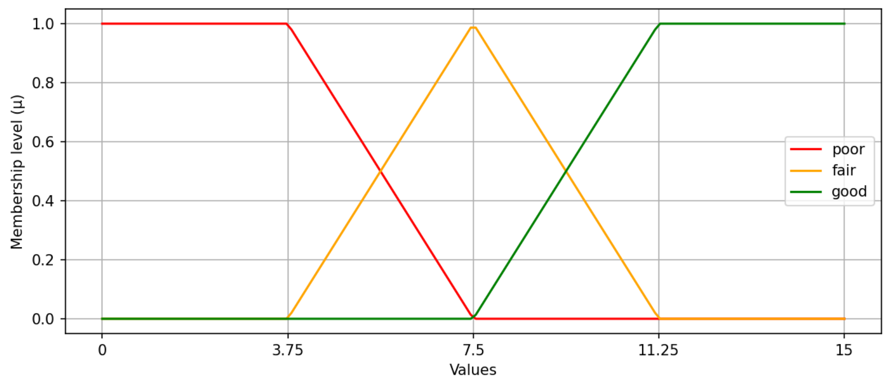
$$\mu_{\text{good}}(x) = \begin{cases} 0, & x \le 12,5 \\ \frac{x-12,5}{18,5-12,5}, & 12,5 < x < 18,75 \\ 1, & x \ge 18,75 \end{cases} \tag{8}$$

3.1.2 Membership Functions for the Test on the Derivative of Integral Functions

For the output variable representing the test on the derivative of integral functions, three fuzzy linguistic categories are defined: poor, fair, and good. Each category is represented by a distinct membership function: the poor set is modeled using a decreasing linear function, the fair set uses a symmetric triangular function, and the good set is modeled with an increasing linear function.

The maximum score for this test is 15 points. Based on the distribution of participants' results, the actual scores ranged from 0 to 15. To transform these values into fuzzy form, the score domain was discretized into three linguistic segments: *poor* [0, 3,75; 7,5]; *fair* [3,75; 7,5; 11,25]; and *good* [7,5; 11,25; 15]. Using Python for visualization, the graphical representation of the membership functions is shown in the following figure.

Figure 2.
Derivative of Integral Functions Test Membership Graph



The membership function formulas for each fuzzy category of the test scores in the *Derivative of Integral Functions* are as follows.

$$\mu_{\text{poor}}(x) = \begin{cases} 1, & x \leq 3{,}75 \\ \frac{7{,}5-x}{7{,}5-3{,}75}, & 3{,}75 < x < 7{,}5 \\ 0, & x \geq 7{,}5 \end{cases} \tag{9}$$

$$\mu_{\text{fair}}(x) = \begin{cases} 0, & x \leq 3{,}75 \\ \frac{x-3{,}75}{7{,}5-3{,}75}, & 3{,}75 < x < 7{,}5 \\ \frac{11{,}25-x}{11{,}25-7{,}5}, & 7{,}5 < x < 11{,}25 \\ 0, & x \geq 11{,}25 \end{cases} \tag{10}$$

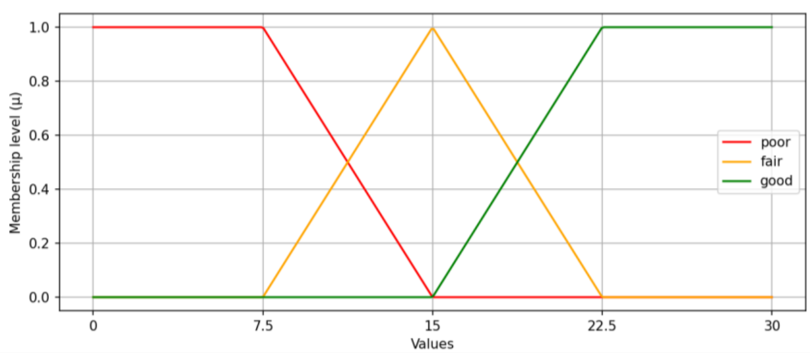
$$\mu_{\text{good}}(x) = \begin{cases} 0, & x \leq 7{,}5 \\ \frac{x-7{,}5}{11{,}25-7{,}5}, & 7{,}5 \leq x < 11{,}25 \\ 1, & x \geq 11{,}25 \end{cases} \tag{11}$$

3.1.3 Membership Functions for the Test on Definite Integrals for the Area under a Single Curve

For the output variable representing the test on the derivative of integral functions, three fuzzy linguistic categories are defined: poor, fair, and good. Each category is represented by a distinct membership function: the poor set is modeled using a decreasing linear function, the fair set uses a symmetric triangular function, and the good set is modeled with an increasing linear function.

The maximum score obtainable for this question is 30 points. Based on the distribution of participants' results, the actual scores range from 0 to 30. To map these scores into fuzzy values, the score domain is discretized into three linguistic segments: *poor* [0; 7,5; 15]; *fair* [7,5; 15; 22,5]; and *good* [15; 22,5; 30]. Using Python for plotting, the graphical representation of the membership functions is shown in the following figure.

Figure 3.
Definite Integrals for the Area under a Single Curve Test Membership Graph



The membership function formulas for each fuzzy category of the test score variable on *Definite Integrals for the Area Under a Single Curve* are as follows.

$$\mu_{\text{poor}}(x) = \begin{cases} 1, & x \leq 7{,}5 \\ \frac{15-x}{15-7{,}5}, & 7{,}5 < x < 15 \\ 0, & x \geq 15 \end{cases} \tag{12}$$

$$\mu_{\text{fair}}(x) = \begin{cases} 0, & x \leq 7{,}5 \\ \frac{x-7{,}5}{15-7{,}5}, & 7{,}5 < x < 15 \\ \frac{22{,}5-x}{22{,}5-15}, & 15 < x < 22{,}5 \\ 0, & x \geq 22{,}5 \end{cases} \tag{13}$$

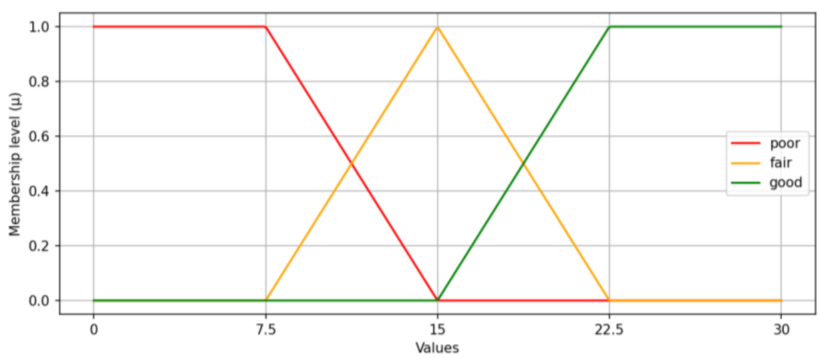
$$\mu_{\text{ good}}(x) = \begin{cases} 0, & x \geq 15 \\ \frac{x-15}{22{,}5-15}, & 15 < x < 22{,}5 \\ 1, & x < 22{,}5 \end{cases} \tag{14}$$

3.1.4 Membership Function of the Test on Definite Integrals for the Area Between Two Curves

For the output variable representing performance in the test on definite integrals for the area between two curves, three fuzzy linguistic categories were defined: poor, fair, and good. Each category is represented by a different membership function: the "poor" set is modeled using a decreasing linear function, the "fair" set uses a symmetric triangular function, and the "good" set is modeled using an increasing linear function.

The maximum score attainable for this test is 25 points. Based on the distribution of participants' results, the actual scores ranged from 0 to 25. To convert these scores into fuzzy values, the score domain was discretized into three linguistic segments: *poor* [0; 7,5; 15]; *fair* [7,5; 15; 22,5]; and *good* [15; 22,5; 30]. Using Python for visualization, the graphical representation of the membership functions is shown in the following figure.

Figure 4.
Definite Integrals for the Area Between Two Curves Test Membership Graph



The membership function formulas for each fuzzy set corresponding to the test scores on definite integrals for the area between two curves are as follows.

$$\mu_{\text{ poor}}(x) = \begin{cases} 1, & x \leq 7{,}5 \\ \frac{15-x}{15-7{,}5}, & 7{,}5 < x < 15 \\ 0, & x \geq 15 \end{cases} \tag{15}$$

$$\mu_{\text{fair}}(x) = \begin{cases} 0, & x \le 7{,}5 \\ \frac{x-7{,}5}{15-7{,}5}, & 7{,}5 < x < 15 \\ \frac{22{,}5-x}{22{,}5-15}, & 15 < x < 22{,}5 \\ 0, & x \ge 22{,}5 \end{cases} \tag{16}$$

$$\mu_{\text{good}}(x) = \begin{cases} 0, & x \le 15 \\ \frac{x-15}{22{,}5-15}, & 15 < x < 22{,}5 \\ 1, & x \ge 22{,}5 \end{cases} \tag{17}$$

3.2 Test Results

After administering the written calculus test and converting the obtained points into scores using **Equation 5**, the resulting scores for each tested topic are as follows.

Table 2.
Test Result

No	Name	Obtained point and score							
		DFC		DIF		DIAC		DIATC	
		Point	Score	Point	Score	Point	Score	Point	Score
1	Aisah Sipahutar	8	25	6	15	10	30	10	30
2	Febri Sihotang	8	25	6	15	10	30	10	30
3	Rully Cesarlin Lumbanraja	8	25	6	15	8	24	7	21
4	Yose Jan Petra Sianipar	8	25	6	15	8	24	6	18
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
43	Yoga Fransisco Purba	0	0	0	0	0	0	0	0

Based on the test results above, the researcher then converted the obtained scores into fuzzy values, also known as degrees of fuzzy membership, as presented in the following subsection.

3.3 Membership Degree and Final Score Recommendation

The degree of membership describes the extent to which a given score belongs to a specific linguistic category such as "poor," "fair," and "good." This value ranges from 0 to 1 and is determined using fuzzy membership functions. This methodology aligns with prior research in decision support systems where numeric input variables are fuzzified into membership degrees categorized as poor, medium (fair), and good using triangular membership functions. Such an approach was clearly demonstrated in a fuzzy expert system for pavement maintenance, where input criteria were fuzzified into these three linguistic categories to support objective and interpretable decision-making (Santos et al., 2022)**,** (Barlybayev et al., 2016)**,** (Annabestani et al., 2020). The degree of membership for each test participant is presented on the table below.

Table 3.
Membership Degree

No	Name	DFC			DIF			DIAC			DIATC		
		P	**F**	**G**	**P**	**F**	**G**	**P**	**F**	**G**	**P**	**F**	**G**
1	Aisah Sipahutar	0	0	1	0	0	1	0	0	1	0	0	1
2	Febri Sihotang	0	0	1	0	0	1	0	0	1	0	0	1
3	Rully Cesarlin Lumbanraja	0	0	1	0	0	1	0	0	1	0	0,2	0,8
4	Yose Jan Petra Sianipar	0	0	1	0	0	1	0	0	1	0	0,6	0,4
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
43	Yoga Fransisco Purba	1	0	0	1	0	0	1	0	0	1	0	0

P:*Poor,* ***F:****Fair,* ***G:****Good*

After obtaining the membership degree values as shown in the table above, the final score was calculated using **Equation 4** to generate the recommendation value. The results of this calculation are presented in the table below.

Table 4.
Final Score Recommendation

No	Name	Membership degree				Recommendation Score
		DFC	**DIF**	**DIAC**	**DIATC**	
		Good	**Good**	**Good**	**Good**	
1	Aisah Sipahutar	1	1	1	1	1
2	Febri Sihotang	1	1	1	1	1
3	Rully Cesarlin Lumbanraja	1	1	1	0.8	0.95
4	Yose Jan Petra Sianipar	1	1	1	0.4	0.85
⋮	⋮	⋮	⋮	⋮	⋮	⋮
43	Yoga Fransisco Purba	0	0	0	0	0

As the final stage of the Tahani fuzzy logic process, the inference rules were determined by the researchers by setting a threshold value. Participants whose crisp output value referred to in this study as the *Final Score Recommendation* is greater than or equal to 0.5 are categorized as having passed the selection test. Overall, a total of eight participants were classified as passing the selection based on the established inference rules.

4. Conclusion

In this study, the Tahani fuzzy logic method was successfully applied to support the selection process of teaching assistant candidates based on their performance in calculus-related test items. By transforming crisp scores into fuzzy membership values across linguistic categories: poor, fair, and good the model effectively captured the uncertainty and variability inherent in human assessment. The fuzzy inference system, guided by predefined rules and membership functions, enabled a more nuanced decision-making process. Participants with a final score recommendation of 0.5 or higher were classified as passing the selection. The results demonstrated that fuzzy logic, particularly the Tahani model, can be a valuable tool in educational decision support systems, offering a transparent and flexible framework for evaluating academic potential.

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6. References

Abdullah, D., Djanggih, H., Suendri, S., Cipta, H., & Nofriadi, N. (2018). Fuzzy Model Tahani as Decision Support System for Employee Promotion. *International Journal of Engineering & Technology*, *7*(2), 88–91. www.sciencepubco.com/index.php/IJET

Abramo, G., D'Angelo, C. A., & Rosati, F. (2015). Selection committees for academic recruitment: does gender matter? *Research Evaluation*, *24*(4), 392–404. https://doi.org/10.1093/reseval/rvv019

Alhasan, W., Ali, M. J., & Shdeed, W. Y. A. (2023). Fuzzy Logic-based Recruitment System: An Innovative Solution for HR Departments. *International Journal of Engineering Research in Africa*, *12*(4). https://doi.org/10.17577/IJERTV12IS040110

Alqodri, F., Agustyana, P. H. P., Masytho, A., Kumalasari, I., Wibowo, F. S., & Prianto, T. (2021). Helpdesk Ticket Support System Based on Fuzzy Tahani Algorithm. *2021 7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*, 521–525. https://doi.org/10.1109/ICEEIE52663.2021.9616744

Annabestani, M., Rowhanimanesh, A., Mizani, A., & Rezaei, A. (2020). Fuzzy descriptive evaluation system: real, complete and fair evaluation of students. *Soft Computing*, *24*(4), 3025–3035. https://doi.org/10.1007/s00500-019-04078-0

Arslan Namli, N., & Şenkal, O. (2018). Using the Fuzzy Logic in Assessing the Programming Performance of Students. *International Journal of Assessment Tools in Education*, *5*(4), 701–712. https://doi.org/10.21449/ijate.429123

Barlybayev, A., Sharipbay, A., Ulyukova, G., Sabyrov, T., & Kuzenbayev, B. (2016). Student's Performance Evaluation by Fuzzy Logic. *Procedia Computer Science*, *102*, 98–105. https://doi.org/10.1016/j.procs.2016.09.375

Doz, D., Felda, D., & Cotič, M. (2022a). Assessing Students' Mathematical Knowledge with Fuzzy Logic. *Education Sciences*, *12*(4), 266. https://doi.org/10.3390/educsci12040266

Doz, D., Felda, D., & Cotič, M. (2022b). Combining Students' Grades and Achievements on the National Assessment of Knowledge: A Fuzzy Logic Approach. *Axioms*, *11*(8), 359. https://doi.org/10.3390/axioms11080359

Faizi, S., Rashid, T., Sałabun, W., Zafar, S., & Wątróbski, J. (2018). Decision Making with Uncertainty Using Hesitant Fuzzy Sets. *International Journal of Fuzzy Systems*, *20*(1), 93–103. https://doi.org/10.1007/s40815-017-0313-2

Gerhana, Y. A., Maylawati, D. S., & Syukur, G. M. (2018). Fuzzy Tahani Algorithm and REST Web Service for Tourist Destination Recommendation. *2018 6th International Conference on Cyber and IT Service Management (CITSM)*, 1–6. https://doi.org/10.1109/CITSM.2018.8674358

Li, X. (2025). Using fuzzy decision support to create a positive mental health environment for preschoolers. *Scientific Reports*, *15*(1), 12339. https://doi.org/10.1038/s41598-025-96543-0

Lima, J. F., Patiño-León, A., Orellana, M., & Zambrano-Martinez, J. L. (2025). Evaluating the Impact of Membership Functions and Defuzzification Methods in a Fuzzy System: Case of Air Quality Levels. *Applied Sciences*, *15*(4), 1934. https://doi.org/10.3390/app15041934

Liu, Q. (2014). Application of Fuzzy Optimization Theory for the Decision of Talents Recruitment in Universities. *Applied Mechanics and Materials*, *631–632*, 1391–1395. https://doi.org/10.4028/www.scientific.net/AMM.631-632.1391

Moratti, S. (2020). Do Low-Openness, Low-Transparency Procedures in Academic Hiring Disadvantage Women? *Social Sciences*, *9*(6), 89. https://doi.org/10.3390/socsci9060089

Nurlayli, A., Adji, T. B., Permanasari, A. E., & Hidayah, I. (2017). Tahani model of fuzzy database for an adaptive metacognitive scaffolding in Hypermedia Learning Environment (Case: Algorithm and structure data course). *2017 International Conference on Sustainable Information Engineering and Technology (SIET)*, 358–363. https://doi.org/10.1109/SIET.2017.8304164

Pelissari, R., Oliveira, M. C., Abackerli, A. J., Ben-Amor, S., & Assumpção, M. R. P. (2021). Techniques to model uncertain input data of multi-criteria decision-making problems: a literature review. *International Transactions in Operational Research*, *28*(2), 523–559. https://doi.org/10.1111/itor.12598

Rao, C. J. (2013). Fuzzy Decision Method for Selecting Civil Servants. *Applied Mechanics and Materials*, *415*, 276–279. https://doi.org/10.4028/www.scientific.net/AMM.415.276

Rizaldi, Anggraeni, D., Syah, A. Z., Kholiq, A., & Agus, R. T. A. (2021). Decision Support System Using Fuzzy Logic Method of Tahani Model for Student Selection. *Journal of Physics: Conference Series*, *1783*(1), 012011. https://doi.org/10.1088/1742-6596/1783/1/012011

Sadiq, H., Barnes, K. I., Price, M., Gumedze, F., & Morrell, R. G. (2019). Academic promotions at a South African university: questions of bias, politics and transformation. *Higher Education*, *78*(3), 423–442. https://doi.org/10.1007/s10734-018-0350-2

Santos, J., Torres-Machi, C., Morillas, S., & Cerezo, V. (2022). A fuzzy logic expert system for selecting optimal and sustainable life cycle maintenance and rehabilitation strategies for road pavements. *International Journal of Pavement Engineering*, *23*(2), 425–437. https://doi.org/10.1080/10298436.2020.1751161

Sitohang, N. S., Isa Irawan, M., Saragi, H. S., Saragih, A., & Simanjuntak, R. (2023). Prioritizing Load Break Switch Placement: Application of Fuzzy AHP-TOPSIS Approaches. *2023 IEEE 3rd International Conference in Power Engineering Applications (ICPEA)*, 32–37. https://doi.org/10.1109/ICPEA56918.2023.10093205

Verina, W., Fauzi, M., Nasari, F., Tanjung, D. H., & Iriani, J. (2018). Decision Support System for Employee Recruitment Using Multifactor Evaluation Process. *2018 6th International Conference on Cyber and IT Service Management (CITSM)*, 1–4. https://doi.org/10.1109/CITSM.2018.8674277