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A FUZZY LOGIC DECISION SUPPORT SYSTEM FOR UNIVERSITY STUDENT DROPOUT ASSESSMENT

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ABSTRACT

Student dropout continues to be an issue in universities, which has a negative impact on the academic performance of students and the reputation of educational institutions. Since the dropout decision is affected by multiple factors like academic performance, financial situation, stress, and self-motivation, the status of these factors can be highly uncertain, subjective, and conventional assessment methods cannot consider this impreciseness. This study designed a fuzzy logic–based decision support system approach to account for the risk of student dropout in a flexible and human-like way. The purpose of this study was to assess the potential risk of a student dropout decision by taking four key input variables: Cumulative Grade Point Average (CGPA), Financial Stability, Stress level, and Self-motivation. The output variable of the system is Dropout Risk Level. A Fuzzy Inference System (FIS) using the Mamdani inference method was developed, which was implemented using the MATLAB Fuzzy Logic Toolbox. Each input variable was represented using three fuzzy linguistic terms (Low, Medium, and High) and triangular membership functions. Fuzzy IF–THEN rules were constructed based on the researcher's expertise and assistance from experienced lecturers. Data were collected using structured questionnaires distributed to students.

Keywords: *Fuzzy Inference System, Fuzzy Logic, Mamdani Method, Student Dropout.*

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1. Introduction

Education is a fundamental societal pursuit, but students' dropping out is a considerable challenge for educational institutions everywhere. In the case of universities, high dropout rates lead to disruptions for individual students, resources and unrealized potential for the institution and, at a socio-economic level for the whole society (Nurmalitasari *et al*., 2023). The increased student dropout rate has negatively affected the university's reputation, leading to reduced student enrolment, decreased university revenue, financial losses for the country, and a rise in social issues among students (Roslan *et al*., 2024). According to Xavier and Meneses (2020), over the last two decades, people have been paying more attention to why students drop out of online higher education (OHE) programs because the dropout rates are much higher compared to face-to-face programs.

There exist several reasons, such as academic performance to financial problems, social integration, and even psychological issues, giving rise to students' decisions to drop out of their studies much before time (Zając *et al*., 2023). According to Núñez-Naranjo (2024), an overview of Ecuador University dropout rates that they vary between first year (12%-15%) and second year (25%-30%) (Buenaño *et al*., 2023). Also, these should be answered by looking into creative and systematic ways that help in finding at-risk students in the early stage and then setting up interventions as the right precautionary measures.

Fuzzy logic was selected in this study because student assessment involves academic and personal factors that may contain uncertainty and subjectivity (Izzati *et al*., 2025). The Mamdani approach is suitable for integrating quantitative and qualitative information in educational decision-making (Agustin *et al*., 2025). Linguistic variables and membership functions allow uncertain conditions to be represented gradually rather than using only rigid numerical boundaries (Anapalı Şenel *et al*., 2025). This is particularly relevant to factors such as stress and motivation, which have been represented as linguistic inputs in fuzzy-based student assessment (Pathak, 2025). Moreover, Mamdani fuzzy systems provide interpretable IF–THEN rules that make the reasoning behind an assessment easier to understand (Carrasco-Garrido *et al*., 2025). Therefore, the Mamdani Fuzzy Inference System was selected to integrate CGPA, financial stability, stress level, and self-motivation in assessing student dropout risk.

2. Research Methodology

The following section details the methodology and criteria to be used behind the elaborate process outlining the creation, growth and testing of a fuzzy logic-based decision support system that focuses on estimating the risks which can potentially lead to the loss of a student. This study aims to give a well-rounded understanding of the complex issue of student dropouts by combining both numbers and personal experiences. By using diverse methods, it thoroughly analyzes the reasons behind dropouts, looking at measurable factors like attendance and grades alongside more personal aspects like motivation and stress levels.

Decision-making is a vital process of achieving a desired outcome by evaluating a set of alternatives against specific criteria under consideration (Hanif *et al*., 2013, 2024). This work relies heavily on fuzzy logic because of its adaptive capacity regarding rather vague and precise imprecise information which often characterizes everyday life (Aggarwal *et al*., 2022; Luo *et al*., 2023). This system acquires the ability to tolerate ambiguity which is commonly found to not exist in permissive systems, which aid in a wide variety of circumstances. Rather, it facilitates the evaluation of parameters like low motivation and moderate stress. Many of these effects can be beneficial for the decision-making process, as they allow for better representation of human thought in the design and greater practicality (Mouedden *et al*., 2022). Methodology further applies to problems in predicting dropouts. These problems include attempting to quantify subjective parameters, the relationships among numerous factors, and the need to

predict desired outcomes. The process involves several key stages like collecting data, developing the fuzzy inference system, creating rules, and validating the system.

2.1 Fuzzy Logic Model Development

A Fuzzy Inference System (FIS) is the computational framework used to evaluate and predict student dropout risks based on various input factors. For this study, the FIS is designed using Mamdani inference, which provides interpretability and aligns with educational contexts where qualitative reasoning is essential. Figure 1 shows the process, including input, processing, and output stages. It helps to illustrate how data flows and how decisions are made within the system.

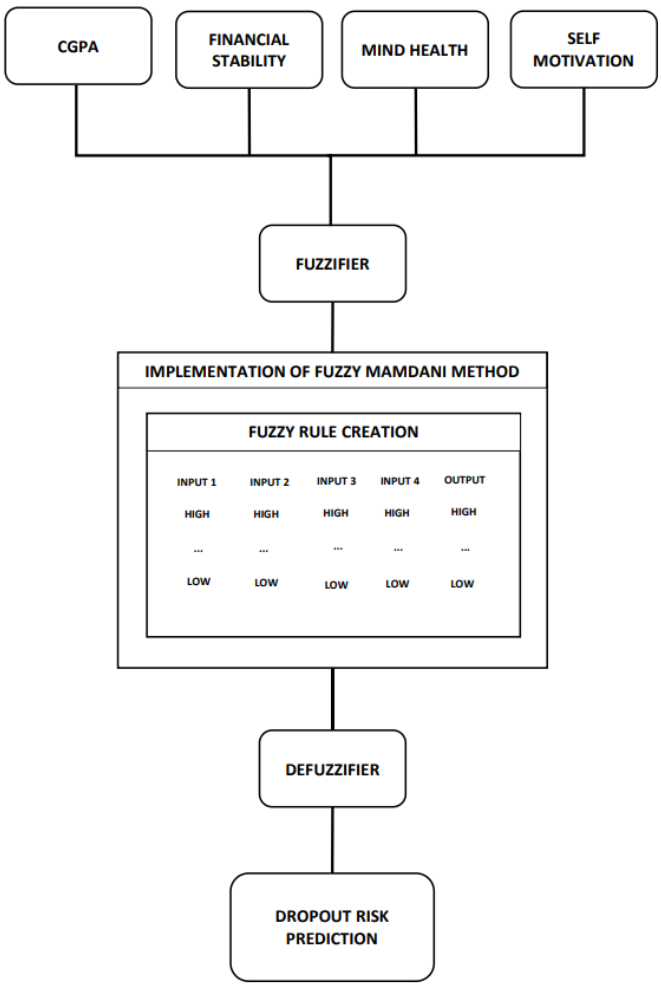


Figure 1. Flowchart of Student Dropout Risk Assessment by Fuzzy Logic System.

i) *Fuzzification:*

A Fuzzification Inference Unit facilitates the entry of crisp and precise input data into the system's fuzzy logic decision making process. Membership functions evaluate input values into fuzzy linguistic variables that include "low," "medium" and "high." Fuzzification establishes an essential process that activates system abilities to process vague and uncertain inputs making FIS unique from standard pure numerical techniques. Fuzzification Inference Unit serves as the interface that transforms precise input data to the fuzzy logic decision making process of the system. The procedure known as fuzzification serves to activate the system's ability to process unclear and uncertain data into its decision-making process. Thus, fuzzification stands out as FIS' main difference from conventional numeric-based systems.

ii) *Knowledge Base:*

As stated by Saatchi (2024), Knowledge Base, as standing in the center of FIS, is the repository of the intelligence of the system. It constitutes two basic components: Data Base and Rule Base. The Data Base recognizes the membership functions and other parameters authorizing the fuzzification and defuzzification processes that make the system able to interpret and manipulate fuzzy data. The Rule Base, on the other hand, contains the set of linguistic rules, much like humans' reason about complex situations in which humans think.

Type of IF-THEN rules:

a. Single-Rule Structure.
   Standard Fuzzy Rules: These rules have a simple structure, typically in the form of "IF X is A THEN Y is B," where X and Y are variables, and A and B are fuzzy sets.
   Example: IF the temperature is high THEN the fan speed is fast.

b. Multiple Antecedents.
   Conjunction Rules: These rules involve multiple conditions in the antecedent, often connected by logical operators (AND, OR).
   Example: IF temperature is high AND humidity is high THEN fan speed is very fast.

c. Multiple Consequents.
   Disjunction Rules: These rules can have multiple outcomes in the consequent, allowing for a range of outputs based on the same antecedent.
   Example: IF temperature is medium THEN fan speed is medium OR air conditioning is on.

iii) *Inference Engine:*

A (FIS) consists of a rule base, which holds important expert knowledge and reasoning to follow in making decisions. It rules an input variable to an output decision using straightforward IF-THEN rules, expressed in everyday language, which connects the input variables to output decisions. Rule base is important in the context of assessing the drop out risk of university students. It is the amalgamation of several factors (a student's academic performance, attendance and motivation) and predicts how likely a student will leave school. This is especially useful if you have partial (or incomplete) information. As such the rule reflects real-world insight into how these factors interact to drive the risks of dropping out. As stated by Putri and Saputro (2021), fuzzy logic tools such as the AND, OR, and NOT are applied to the inputs and then an output is provided which signals the level of the risk. The rules are simple and easy to read so education experts can easily review and modify them, so they remain logical and effective.

iv) *Defuzzification:*

The fuzzy output of the FIS is linked to the final step of the FIS, which is the Defuzzification Inference Unit and finally to some crisp, accurate possible output that the system can output as. Special defuzzification techniques include Center of Gravity (COG) or Mean of Maximum (MOM), and this fuzzy output is transformed into a distinctly actionable result that may then be utilized in different applications. One of the most popular defuzzification techniques in the fuzzy logic systems is the Centroid method, also popularly known as the (COG) method. It finds the centroid (the centre of mass) of the fuzzy set which represents the output variable and calculates defuzzified output.

- Centroid method (Na & Jing, 2012)

$$z^* = \frac{\int z u_A(z)\, dz}{\int u_A(z) dz} \tag{1}$$

2.2 Variables Overview and Linguistic Variables

The variable overview indicates the 4 main criteria used to measure the risk of student dropout assessment within the fuzzy logic framework.

Step 1: **Define Variables**
The first step involved identifying the main input variables that influence student dropout which is CGPA, Financial Stability, Self-Motivation, and Stress Level. Lastly, we have one output variable, Dropout Risk Level. Each variable is represented by linguistic terms (Low, Medium, High) and modeled using triangular membership functions.

Step 2: **Determine Criteria and Gather Expert Input**
The fuzzy rules and criteria were formulated based on the researcher's expertise and supported by feedback from experienced lecturers from the Faculty of Computer and Mathematical Sciences, UiTM. These experts helped confirm that the selected variables were relevant to the dropout problem. The summary of criteria is shown in Table 1.

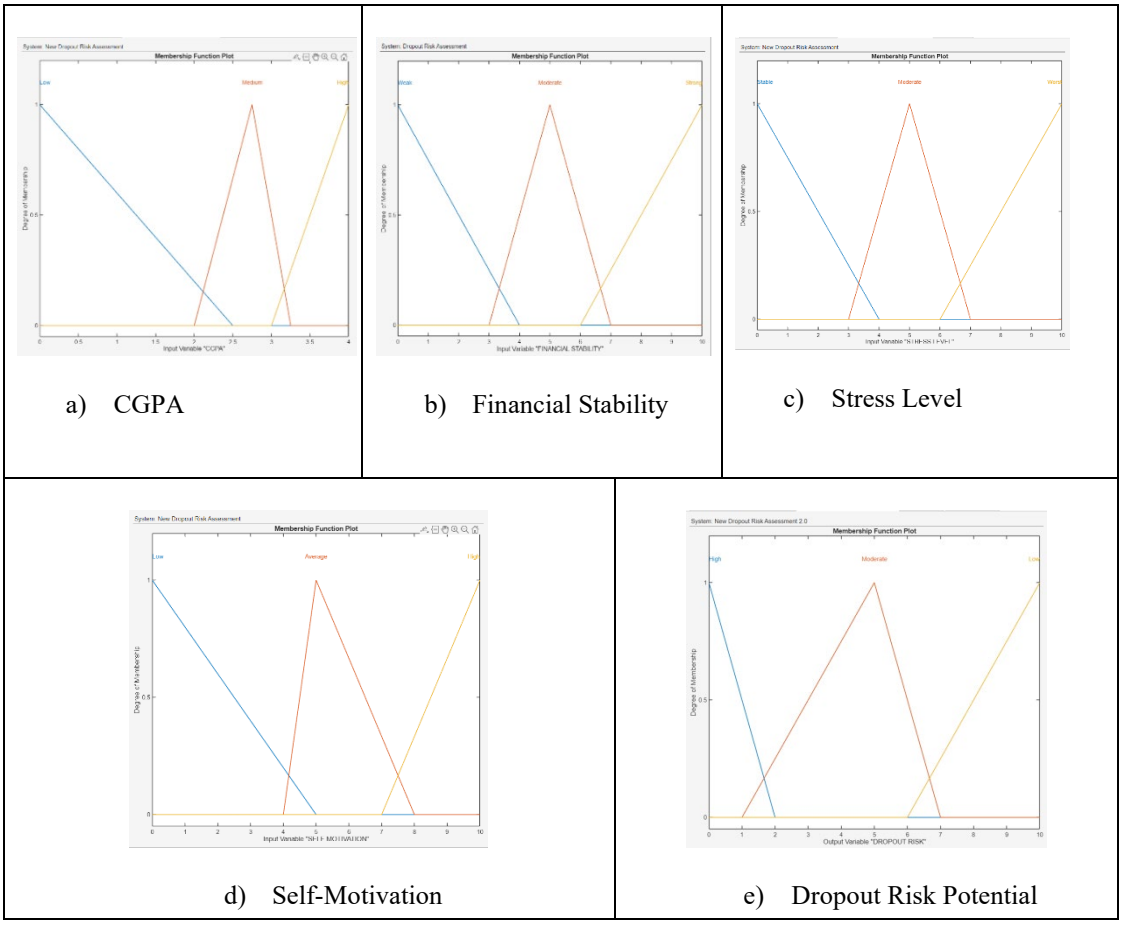
Table 1. Fuzzy Logic Linguistic Variables and Description

Linguistic Variable	Linguistic Value	Real Life Range	Triangular Membership Function	Description
CGPA	Low	0 – 2	[0, 0, 2]	Students have poor academic performance (e.g., struggling in coursework or exams)
	Medium	1.75 – 3.25	[1.75, 2.5, 3.25]	Students perform fairly but not consistently strong
	High	3 - 4	[3, 4, 4]	Students maintain strong academic results with high grades
Financial Stability	Low	0 - 4	[0, 0, 4]	Student faces financial hardship and may need to work part-time to support studies
	Medium	5 - 7	[3, 5, 7]	Students have some financial support but still experience occasional constraints
	High	6 - 10	[6, 10, 10]	Students are financially secure with no major economic burden
Stress Level	Low	0 - 4	[0, 0, 4]	Students are mentally healthy and handles stress well
	Medium	3 - 7	[3, 5, 7]	Students experience manageable levels of stress
	High	6 - 10	[6, 10, 10]	Students are highly stressed, overwhelmed, and emotionally drained
Self-Motivation	Low	0 - 5	[0, 0, 5]	Students lack motivation, are easily distracted, and show poor study habits
	Medium	4 - 8	[4, 5, 8]	Student shows effort but may be inconsistent in staying motivated
	High	7 - 10	[7, 10, 10]	Students are driven, goal-oriented, and persistent even during challenges
Dropout Risk Potential	High	0 - 2	[0, 0, 2]	Students face very high dropout risk due to severe academic, financial, or motivational issues.
	Medium	1 - 7	[1, 5, 7]	Students show some risk; challenges exist but can be managed with proper support.
	Low	6 - 10	[6, 10, 10]	Students have strong stability and motivation, with low possibility of dropping out.

The numerical ranges and membership functions were determined according to the measurement scale and characteristics of each variable, with consideration of expert input. CGPA uses a 0–4 academic scale, while Financial Stability, Stress Level, and Self-Motivation are evaluated on a 0–10 scale; therefore, their numerical ranges are not directly comparable. Overlapping triangular membership functions were used to provide gradual transitions between the Low, Medium, and High linguistic categories rather than applying strict boundaries. The specific ranges for the subjective variables were determined based on the interpretation of their

measurement scales and feedback from experienced lecturers involved in the development of the fuzzy model.

Step 3: **Develop Fuzzy Membership Functions in MATLAB**
Using **MATLAB Fuzzy Logic Toolbox**, membership functions were created for each input and output variable according to the defined numerical ranges as shown in Figure 2.



a) CGPA b) Financial Stability c) Stress Level

d) Self-Motivation e) Dropout Risk Potential

Figure 2. Triangular Membership Functions for Each Variable.

Step 4: **Construct Fuzzy Rule Base for the Output of Dropout Risk Potential**
In MATLAB, fuzzy rules use simple "If-Then" statements to show how various input factors affect output. The rules use terms such as Low, Medium, and High to describe how real-world indicators in human terms affect a person's final conclusions. For example, one rule might state: "If CGPA is Low and Stress Level is High, then Dropout Risk is High", meaning that a student who has experienced poor academic performance and has high levels of stress has a greater risk of dropping out. All the rules work together in the system to strengthen the overall prediction of student dropout risk based on aspects of the person's academic and personal situations. There are a total of 81 rules for this system as shown in Figure 3. The total number of possible fuzzy rules is determined by multiplying the number of linguistic terms for each input variable. Since the system consists of four input variables, with three linguistic terms for each variable, the total number of possible rules is calculated as:

$$R = L_1 \times L_2 \times L_3 \times L_4 \quad (2)$$

where R represents the total number of possible fuzzy rules, and L_i represents the number of linguistic terms for each input variable.

System: New Dropout Risk Assessment

Add All Possible Rules | Clear All Rules

	Rule	Weight	Name
1	If CGPA is Low and FINANCIAL STABILITY is Weak and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is Critical	1	rule1
2	If CGPA is Medium and FINANCIAL STABILITY is Weak and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is ...	1	rule2
3	If CGPA is High and FINANCIAL STABILITY is Weak and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is Critical	1	rule3
4	If CGPA is Low and FINANCIAL STABILITY is Moderate and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is ...	1	rule4
5	If CGPA is Medium and FINANCIAL STABILITY is Moderate and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK...	1	rule5
6	If CGPA is High and FINANCIAL STABILITY is Moderate and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is ...	1	rule6
7	If CGPA is Low and FINANCIAL STABILITY is Strong and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is Criti...	1	rule7
8	If CGPA is Medium and FINANCIAL STABILITY is Strong and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is ...	1	rule8
9	If CGPA is High and FINANCIAL STABILITY is Strong and STRESS LEVEL is Stable and SELF MOTIVATION is Low then DROPOUT RISK is Crit...	1	rule9
10	If CGPA is Low and FINANCIAL STABILITY is Weak and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK is C...	1	rule10
11	If CGPA is Medium and FINANCIAL STABILITY is Weak and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK i...	1	rule11
12	If CGPA is High and FINANCIAL STABILITY is Weak and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK is C...	1	rule12
13	If CGPA is Low and FINANCIAL STABILITY is Moderate and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK i...	1	rule13
14	If CGPA is Medium and FINANCIAL STABILITY is Moderate and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RI...	1	rule14
15	If CGPA is High and FINANCIAL STABILITY is Moderate and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK ...	1	rule15
16	If CGPA is Low and FINANCIAL STABILITY is Strong and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK is ...	1	rule16
17	If CGPA is Medium and FINANCIAL STABILITY is Strong and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK...	1	rule17
18	If CGPA is High and FINANCIAL STABILITY is Strong and STRESS LEVEL is Moderate and SELF MOTIVATION is Low then DROPOUT RISK is ...	1	rule18
19	If CGPA is Low and FINANCIAL STABILITY is Weak and STRESS LEVEL is Worst and SELF MOTIVATION is Low then DROPOUT RISK is Critical	1	rule19
20	If CGPA is Medium and FINANCIAL STABILITY is Weak and STRESS LEVEL is Worst and SELF MOTIVATION is Low then DROPOUT RISK is C...	1	rule20

Figure 3. Part of Fuzzy Rule in MATLAB.

Step 5: **Applying Mamdani Inference Process**

In this stage, the fuzzy inference was done by the Mamdani method. This method is commonly used, as it requires a reasonable easy computation and models human reasoning well. At this stage, the fuzzy values of input are then evaluated by IF–THEN rules and, for each rule, the degree of truth is calculated by using the minimum (AND) operator, which takes the minimum value of the membership value of all input conditions in the rule. The fuzzy output of all firing rules is combined by using the maximum or (OR) operator, resulting in a fuzzy output as a dropout risk. This output shows the impact of all input conditions and their corresponding rule strengths.

Step 6: **Defuzzification (Output Conversion)**

The fuzzy output was made into a clear number by using the centroid method in Equation (1). This method gives one number which shows the predicted dropout risk on a 0 – 10 scale. This system was tested with three student datasets to see how changing the input values would change the dropout risk output. The outcomes were looked at to make sure that the answers made sense, like when a high stress value, and a small CGPA value should give a high dropout risk. Table 2 presents the input values for each criterion from three student respondents involved in this assessment.

Table 2. Criteria Score for Each Candidate

Criteria	Candidates	Score
CGPA	Student 1	3.86
	Student 2	3.05
	Student 3	2.11
Financial Stability	Student 1	5.83
	Student 2	10
	Student 3	5.0
Stress Level	Student 1	8.75
	Student 2	8.75
	Student 3	6.875
Self-Motivation	Student 1	7.50
	Student 2	8.125
	Student 3	6.25

Table 3 displays the outcomes derived from the fuzzy system in MATLAB for the four criteria stated earlier.

Table 3. Outcome of the Derived Fuzzy System for Student Dropout Potential

Fuzzy System	Candidates	Output
Dropout Risk Potential	Student 1	8.19
	Student 2	8.28
	Student 3	4.73

3. Criteria to Be Used

The selection of the four input criteria in this study is supported by previous research on factors associated with university student dropouts (Palomino & Ortega, 2023; Santos *et al*., 2024; Valencia-Arias *et al*., 2026). Academic performance, including CGPA and grades has been identified as an important factor associated with student dropout (Andrade Vera *et al*., 2026). Financial difficulties may also increase students' vulnerability to dropout by creating financial pressure and affecting their academic engagement (Andrade Vera *et al*., 2026). In addition, stress has been associated with higher dropout intention and lower academic engagement among university students (Sinval *et al*., 2024). Student motivation is also an important factor, as higher autonomous motivation has been associated with lower dropout intentions (Tesi *et al*., 2025). Therefore, CGPA, Financial Stability, Stress Level, and Self-Motivation were selected as the four input variables for assessing student dropout risk in this study.

1) Academic Performance (CGPA)
2) Financial Stability
3) Stress Level
4) Self-Motivation

4. Results and Discussions

The fuzzy logic model calculated the likelihood for three student respondents, Student 1, Student 2 and Student 3 to drop out of the university. Outputs highlighted the distinct identification of each student based on their unique academic, financial and psychological circumstances. The dropout risk score for Student 1 was 8.19, followed by Student 2 with a dropout risk score of 8.28, both in the "Low Risk" range. Student 2 was unique because her CGPA is 3.05 but her scores in the key input criteria in terms of financial situation, self motivation and stress response were comparatively stronger. Therefore, Student 2 achieved a low dropout risk rating in this assessment despite her CGPA not being in the highest range.

For Student 3, his dropout risk was recorded at 4.73, the "Medium Risk" range. The medium risk indicates that while Student 3 may be performing satisfactorily in some areas, other challenges perhaps due to stress management or financial situation contribute to a greater overall risk. The overall dropout risk calculated a composite of all input criteria which evaluates risk even if each individual factor may not indicate a risk.

5. Conclusion

On the other hand, this research demonstrated its main achievement by developing a fuzzy logic system that assesses risk to a concept, in this case, the risk of student dropout using a variety of key criteria. The four input variables CGPA, financial stability, stress level, and self-motivation, were selected to provide a reasonable attitude to the key academic, social, and personal issues surrounding continuity of student retention. When applied to the input data, the fuzzy logic system provided reasonable results. For instance, Student 1 was only scored 8.19 risk of dropping out, while Student 2 was only scored 8.28 for the risk of dropping out, both being classified as “Low Risk” of dropping out. These scores were possible through higher self-motivation, financial stability, and moderate stress levels in their studies. In comparison, Student 3 was only scored at 4.73 and in the “Medium Risk" category, as there may have been higher levels of stress or worse CGPA background but with a stable stress response. Overall, these findings prove that the fuzzy logic system is a quality tool to assess risk through the incorporation of a variety of inputs whilst depicting various outcomes realistically as required for risk assessments in educational practices with students. For future research, the proposed fuzzy logic model should be tested and validated using a larger and more diverse population of university students. This would help evaluate the model's reliability and applicability across different student populations and educational settings.

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Author Contribution

Adam Aiman A Hamid was responsible for the data curation, experimentation, visualization, and writing the draft of the manuscript. Harliza Mohd Hanif was responsible for the conceptualization, methodology, and supervision of the project. Siti Rahimah Batcha, Nur

Zafirah Mohd Sidek, Noratika Nordin and Norain Alwi were responsible for manuscript formatting, editing and proofreading.

Declaration of Generative AI in the Writing Process

During the preparation of this work, the authors did not use any AI-assisted technologies.

Data Availability/Supplementary Materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Statement

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of Universiti Teknologi MARA.

Conflict of Interest

The authors have no conflicts of interest to declare.

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