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Research Article

Minimum Passing Standard Setting based on Data-Driven Decision Making for English Online Exam using Fuzzy Algorithm

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ABSTRACT

This study aims to establish a minimum standard for student performance in Basic English Language Learning (BELL) through a pre-assessment, the Integrated Standard English Exam (i-SEE). The i-SEE evaluates five key areas: listening, reading, structure and grammar, social skills, and picture/audio comprehension, each consisting of 10 questions, for a total of 50 questions. The test results are presented in tabular form, detailing the performance in each assessed aspect. The recapitulated results serve as the basis for developing a personalized Learning Plan (LP), guiding both tutors and students to focus on areas where students show weaknesses. This ensures a more targeted and comprehensive learning experience. The research employs the Fuzzy Tsukamoto algorithm to determine the minimum standard student scores. The study follows a Data Driven Decision Making approach, leveraging initial data to inform the analysis. The results indicate that the minimum standard for each material is 12.46 out of 20, while the overall minimum standard is 57.36 out of 100. The accuracy of the fuzzy calculation was evaluated using the Mean Absolute Percentage Error (MAPE), yielding 92.08% for category-based calculations and 99.49% for overall calculations. These findings highlight the efficacy of fuzzy logic in setting minimum performance standards and enhancing the precision of educational assessments.

Keywords: test, minimum standard score, Fuzzy Tsukamoto, integrated Standard English Exam

INTRODUCTION

English, like other languages, has many aspects to learn. Apart from the four main language skills (listening, speaking, reading, and writing), there are also rules related to sentence structure (structure and grammar), colloquial forms in relationships (social skills), understanding context (contextual understanding), and others. This is certainly not an easy thing to learn, especially for those who are less interested in languages. However, Indonesian pupils and students are required to learn at least 2 languages during their education phase, i.e., Indonesian and English. Current global demands require the ability to speak English as one of the main skills that must be mastered. But in fact, Indonesia is still ranked 79th out of 113 countries (considered low proficiency) in the 2024 English First English Proficiency Index (EF EPI) (EF, 2024). In the Southeast Asia region, Indonesia is ranked fifth out of nine countries surveyed, behind Singapore, the Philippines, Malaysia, and Vietnam.

In terms of education, there have been several changes to the educational curriculum made by the Indonesian Ministry of Education and Culture since 1947-2013, all of which placed English in the curriculum. During this period, until now, there have been several techniques and strategies used by teachers to achieve their goals, such as contextual teaching, affective strategies, and metacognitive strategies (Hapsari, 2019)(Muttaqin & Chuang, 2022). However, to make this happen, they must first face various challenges (Sakkir et al., 2021)(Siew Eng & Jiaxi, 2022).

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The problems that occur include the learning and exam system not being able to accommodate all types of skills needed to master the language. The existence of the Communicative Language Teaching (CLT) system does make learning more dynamic, but it still suffers from several aspects, such as student motivation, life background, number of students, curriculum, and examination system (Kasumi, 2015)(Paul, 2022). Examination systems that combine various aspects of language learning into one form of examination only produce one complete score, without providing scoring for each aspect tested. With a method like this, students will never know their specific strengths and weaknesses, so their abilities cannot develop and broaden.

The hypothesis presented here is that students need to follow a series of initial learning programs called Basic English Language Learning (BELL). This program begins with an initial test (pre-test) on basic English skills called the Integrated Standard English Exam (i-SEE) before they start studying. i-SEE is an online English test that targets five basic English skills (listening, reading, grammar/structure, social skills understanding, and picture/video perception) at beginner level. This question is a standard test for understanding basic English which is determined jointly based on the theory of Arifin (Arifin, 2012) and the HOTS English Preparation Module (Cahyana & Sugiarto, 2019). This test is intended to standardize English language skills for students so that lecturers can map their weaknesses and strengths.

The results of this test are displayed in table form for each assessment aspect category along with the minimum standard score. The results of the recapitulation will be used as a basis for determining scheduling and the next Learning Plan (RP). The Fuzzy Tsukamoto algorithm is applied to provide precise and appropriate minimum score calculation results. This display consists of a minimum score per category (test material), and overall. By dividing passing standards into categories/materials, tutors will be able to focus only on subjects that become students' weaknesses, so that the learning process can be more detailed and focused. This makes this online-based test a smart system and results data can be retrieved at any time if needed. The overall minimum score results are used as the student graduation standard for this BELL program.

A good English test was expressed by Maris (Maris, 2020) who conducted research on the Duolingo English test which can carry out a real-time result ranking system and this test is not based on the characteristics of the participants so it can be applied to various different groups with test participants with different backgrounds. This type of Duolingo test was also studied by Burr et al. (Settles et al., 2020) with a machine learning-based information system approach. It was explained that the proficiency scale was determined based on existing standards and using linguistic models to assess the level of difficulty of the questions. The results obtained are that the type of online test is significantly aligned with the type of English language tests previously used in the world.

In general, online learning and exam processes have become commonplace nowadays, after the recent Covid-19 pandemic. Ima and Jannah (Fitriyah & Jannah, 2021) conducted research on the effects of online exams and assessments from the perspective of participants and tutors. The result obtained is that administratively, this form of exam can cut several stages, such as the process of duplicating questions, scoring, etc. Meanwhile, from a student's perspective, this type of online test makes the process easier and more flexible, reduces anxiety and increases self-confidence. The same thing was also mentioned by Firdaus (Firdaus et al., 2022) who said that the regular use of several online formative assessment tools during English language teaching and learning such as Quizizz, Google Form, Socrative, Kahoot!, and Microsoft Teams will form a dynamic learning and exam ecosystem. and flexible, improve the computer and digital literacy skills of the perpetrators, and speed up processes related to assessing student abilities.

Data Driven Decision Making (DDDM) has been used in the world of Education and there are several studies that have been conducted related to this, including (Doğan & Demirbolat, 2021) which examines DDDM from the point of view of its validity and reliability. The results of a study on 179 school administrators in Turkey show that DDDM is a measurement tool that is able to produce valid and reliable measurements and can be used in measuring various needs in schools. Furthermore, (Gaftandzhieva et al., 2023) shows that schools have used a lot *of data analytics tools* including for data mining, learning method analysis, and *business intelligence* to get inputs, recommendations, and knowledge from education data. DDDM provides affirmation on pedagogical theories, frameworks, and various educational phenomena. Furthermore, Kaspi and Venkatraman (Kaspi & Venkatraman, 2023) who researched the calculation of the results of assessments in universities in Information Technology students in Australia. The results

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of the comparison stated that DDDM was able to provide more accurate results so that it could be used as a basis for developing educational methods in the current education transformation.

In determining the minimum passing score, several related journals include research results from Iswan et al. (Siahaan & Putera, 2017) which focuses on determining employee work suitability using the fuzzy Tsukamoto algorithm which produces the conclusion that the greater the academic potential test score, the greater the work suitability value obtained, and the higher the GPA obtained, the greater the work suitability value. This was also done by Zaaidatunni'mah et al. (Zaaidatunni et al., 2021) who researched determining employee performance appraisals using the Tsukamoto fuzzy algorithm. Nugraha (Nugraha et al., 2019) also used the Tsukamoto fuzzy algorithm to determine journal acceptance as a comparison of manual methods and expert opinions. The results obtained are that this algorithm has a prominent level of accuracy and can be used in the journal acceptance process.

The fuzzy logic method also has another type, namely fuzzy Mamdani. Safik et al. (Omara et al., 2012) compared the Tsukamoto fuzzy method with the Mamdani fuzzy method to determine the recommended value of customer savings deposits. The results obtained indicate that the Tsukamoto fuzzy method has better accuracy. Furthermore, Ayuningtias et al. (Ayuningtias et al., 2017) compared 3 fuzzy methods (tsukamoto, mamdani, and sugeno) to predict the number of new student applicants on a campus. The results show that the fuzzy Mamdani method has a smaller error rate compared to the other two.

Online testing provides many advantages for test administrators (Alrefaai, 2016)(Ayuba & Masae, 2022). Efficiency can be achieved in various aspects of activities, from preparation, implementation, to reporting. This includes the areas of human resources, use of stationery, costs for duplicating questions and answer sheets, and other elements needed to carry out a test activity. The amount of working time can also be reduced a lot due to the automation of the exam system so that work effectiveness can increase. For example, administrators do not need to reproduce exam materials, calculate scores, or even print certificates. This type of test also allows staff and lecturers to conduct tests with aspects that cannot be accommodated by paper-based tests, such as automatic randomization of questions, audio-image questions, and video-based questions. The variety of question package variants can also be increased because human resources can be diverted to this task.

The main idea of this research is to utilize standard English proficiency tests as a basic platform for mapping prospective students' English abilities. The test results/scores will be broken down by category (score breakdown) so that it can be seen in which category the student has strengths and weaknesses. This data is then processed by the application to be used as material for making Learning Plans, especially for students who do not meet standards.

METHOD

This research begins with determining the type of test that will be tested. Focus Group Discussion (FGD) is the method chosen as a means of determining the type of test, test standard, test category, number, points, and level of difficulty of questions, and passing standards. This method was chosen because it can accommodate various input and suggestions so that discussions occur which lead to a better system (William, 2012)(Mishra, 2016). The data treatment and analysis followed the Data Driven Decision Making (DDDM) procedure. The shift in the education paradigm to evident-based education makes the role of DDDM important in various fields of education, starting from the level of decision makers, to teachers/lecturers in the classroom (Zhu, 2018). Because of its database-based nature, DDDM can also be used for various purposes, ranging from increasing innovation and sustainable development of educational institutions, identifying inequalities, both in the field of gender equality and educational attainment, increasing accountability and transparency of educational institutions, to improving learning and student achievement (Nurzen S, 2022).

After conducting an FGD with 6 lecturers who teach English courses from several study programs on campus, the choice was made on the Ordinary Multiple Choice test because it was deemed to fulfil 4 test quality criteria, namely: 1) validity, 2) reliability, 3) distinguishing power, and 4) balance of difficulty level (Hanifah, 2014). The standard test used is the Common European Framework of Reference (CEFR) with a score of lower middle (A2) – Elementary, taking into account the low level of English language skills of the Indonesian people (EF EPI, 2022).

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Furthermore, it was agreed that there were five categories of question material to be assessed, namely: listening, reading, grammar/structure, social skills understanding, and picture/audio perception at the beginner level. There are ten questions/questions in each category with a division of three difficult questions (hard), 4 medium questions (standard), and 3 easy questions (easy), so the total is 50 questions, and each level of difficulty of the questions has a standard point. different. If working on questions is 1 minute/question, then the specified time for working on questions is 60 minutes or 1 hour. The standard results determined are pass and re-learn.

Table 1. Weighting Standard of Test Questions per Category

Level	No. of Questions	Point per Question	Sub-total
Easy	3	1,5	4,5
Standard	4	2	8
Hard	3	2,5	7,5
TOTAL	**10**		**20**

This exam is made using the Fuzzy Tsukamoto algorithm which is used to determine the minimum standard score for the participants. The minimum standard will be divided into 2 parts, namely the minimum standard per material tested, and the minimum standard for the overall score. These results will be grouped based on the category of questions assessed so that later the tutor can determine an appropriate learning plan for their students. The Fuzzy Tsukamoto algorithm was chosen because of its ability to process data with many variables but can provide accurate results. This algorithm solves the problem by forming an if-then rule. In this method, each result of a rule must be substituted by a fuzzy set with a monotone membership function (Muhandhis et al., 2021). The exam was conducted on a group of initial level students (semester 1) of an institute in West Jakarta with a total of 20 people. One group of students takes an initial test (pre-test) with predetermined standards. The results of the exam are then used as initial data in calculating minimum standard scores, both per category and overall.

Because the graduation assessment is based on two references (per category and overall), there will be some results that raise doubts, such as if three categories (of 5) are declared passed, and re-learn in the other two categories, or vice versa. This will of course cause confusion in the overall assessment, because it could be that participants who pass in two categories are declared passed and have pass status in overall, but participants who pass in three categories are declared re-learners in overall. If this is not explained in the results of each category and overall, it will create an average scoring system and the participants' strengths and weaknesses will not be known.

RESULTS AND DISCUSSIONS

The results of the initial exam (pre-test) from 20 students showed mixed results. There are fifty questions with three distinct levels of difficulty (easy-standard-hard) for each category. The detailed values of these groups are as follows:

Table 2. English *Pre-Test* Result

ST ID	LISTENING				READING				GRAMMAR				SOCIAL SKILLS				PICTURE/AUDIO				SUM Σ
	E	S	H	Σ	E	S	H	Σ	E	S	H	Σ	E	S	H	Σ	E	S	H	Σ	
1	2	2	1	9.5	2	1	2	10	3	0	0	4.5	3	2	1	11	3	3	0	10.5	45.5
2	3	4	0	12.5	3	1	0	6.5	2	2	0	7	3	2	2	13.5	3	3	1	13	52.5
3	3	4	1	15	3	3	2	15.5	3	3	1	13	3	4	2	17.5	3	4	2	17.5	78.5
4	3	3	1	13	2	4	1	13.5	3	2	1	11	3	4	0	12.5	3	4	1	15	65
5	2	2	0	7	3	3	0	10.5	3	2	0	8.5	3	3	0	10.5	2	2	0	7	43.5
6	3	3	1	13	3	3	1	13	3	4	0	12.5	3	2	0	8.5	3	2	2	13.5	60.5
7	3	3	0	10.5	3	3	0	10.5	3	3	0	10.5	3	3	1	13	3	3	2	15.5	60
8	3	4	1	15	3	3	2	15.5	3	4	0	12.5	3	3	2	15.5	2	3	2	14	72.5
9	2	0	0	3	3	0	0	4.5	2	0	0	3	2	2	0	7	2	2	1	9.5	27
10	3	4	2	17.5	3	3	3	18	3	3	3	18	3	4	2	17.5	3	4	2	17.5	88.5
11	3	3	3	18	3	3	2	15.5	3	2	2	13.5	3	4	3	20	3	4	3	20	87
12	2	3	1	11.5	2	2	0	7	3	1	0	6.5	3	2	2	13.5	2	3	3	16.5	55
13	2	3	0	9	2	2	1	9.5	1	2	0	5.5	2	2	2	12	2	2	2	12	48
14	2	2	2	12	3	1	0	6.5	3	1	0	6.5	3	3	1	13	3	4	0	12.5	50.5
15	3	1	0	6.5	2	2	2	12	3	2	0	8.5	3	3	0	10.5	3	1	0	6.5	44
16	3	4	0	12.5	2	3	2	14	3	3	1	13	3	2	0	8.5	3	3	1	13	61
17	3	2	1	11	2	2	2	12	2	2	2	12	2	3	2	14	3	3	2	15.5	64.5
18	3	3	2	15.5	3	4	1	15	2	4	0	11	2	4	2	16	2	4	0	11	68.5
19	2	0	0	3	3	0	0	4.5	2	0	0	3	3	2	0	8.5	2	1	2	10	29
20	3	3	0	10.5	2	2	0	7	3	1	0	6.5	3	2	2	13.5	3	4	0	12.5	50

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Value Range

The research input variables were determined by 5 criteria, namely: listening, reading, grammar/structure, social skills understanding, and picture/audio perception, and 1 output variable, the inference result (passed, re-learn). The value per category has a range between 0-20. There are five categories of questions so the range for the total score is 0-100. These things are the determining factors for decision making for making learning plans and are included as input into the Tsukamoto fuzzy system. The value range table is as follows.

Table 3. Value Range per Category

Criteria	Range/Category	Range Overall
K1 (Listening Comprehension)	0-20	
K2 (Reading Comprehension)	0-20	
K3 (Structure/Grammar)	0-20	
K4 (Social Skills Understanding)	0-20	
K5 (Picture/audio Perception)	0-20	
K6 (Test Result)	0-20	0-100

Fuzzification

From the data, the average value per category was taken and then used as the basis for conducting calculations using the fuzzy Tsukamoto formula. The specified minimum and maximum limits are 0 and 20 for calculations per category, and 0 and 100 for overall calculations. Apart from that, the rules of this fuzzy are also determined, i.e., 52 or twenty-five rules. The basic scores for fuzzification calculations are as shown in the table below:

Table 4. Average Score of Participant's Data

Criteria	rScore
K1 (Listening Comprehension)	11.28
K2 (Reading Comprehension)	11.03
K3 (Structure/Grammar)	9.33
K4 (Social Skills Understanding)	12.80
K5 (Picture/audio Perception)	13.13

Fuzzification per Category

Fuzzification calculations for the five variables above use the formula below:

$$Re-learn\ (x) = \begin{cases} 1; & x \leq 20 \\ \frac{(20-x)}{(20-0)} & 0 \leq x \leq 20 \\ 0; & x \geq 0 \end{cases} \quad \text{..... (1)}$$

$$Passed\ (x) = \begin{cases} 0; & x \leq 20 \\ \frac{(x-20)}{(20-0)} & 0 \leq x \leq 20 \\ 1; & x \geq 0 \end{cases} \quad \text{..... (2)}$$

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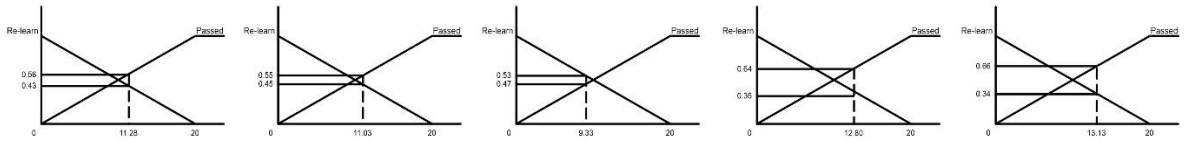
With the formula above, the results of the fuzzification calculation are as follows:

Table 5. Fuzzification Result per Category

Result	K1	K2	K3	K4	K5
μRe-learn (x)	0.4363	0.4488	0.5338	0.3600	0.3438
μPassed (x)	0.5638	0.5513	0.4663	0.6400	0.6563



K1 **K2** **K3** **K4** **K5**

Figure 1. Fuzzification Diagram per Category

Fuzzy Inference

This step is used to determine the α and Z values, where L is Listening, R is Reading, G is Grammar, S is Social Skills, and P is Picture/Audio. In finding the value of α, it is necessary to find intersections between categories in one rule, as in the example of a formula with rule (R1) below:

R1: If L **Re-learn** and R **Re-learn** and G **Re-learn** and S **Re-learn** and P **Re-learn** then **Re-learn.**

α1 = μL Re-learn [X] ∩ R Re-learn [X] ∩ G Re-learn [X] ∩ S Re-learn [X] ∩ Re-learn [X]

= min (μ[0.44] [11.18] ∩ [0.45] [11.03] ∩ [0.53] [9.33] ∩ [0.36] [12.8] ∩ [0.34] [13.1])

= 0.3438

According to the value set membership function (score) in the equation above, an equation is obtained to find the Z value. For example, the following is the calculation of the Z1 value:

$$\frac{Zmax - Z1}{Zmax - Zmin} = Z1 \quad \text{..... (3)}$$

Z1 = Zmax – α1 (Zmax – Zmin)

Z1 = 20 – 0,3438 (20-0)

Z1 = 20 – 6,8

Z1 = 13,1240

Below are shown the results of the overall α and Z calculations as a basis for calculating the minimum score result per category.

Table 6. Rule Base Results

R	α_p	Z	R	α_p	Z	R	α_p	Z	R	α_p	Z	R	α_p	Z
R1	0.3438	13.1240	**R6**	0.3600	4.6080	**R1 1**	0.38	4.5120	**R16**	0.4413	4.9311	**R2 1**	0.3600	4.6080
R 2	0.38	13.1240	**R7**	0.3438	4.5120	**R1 2**	0.38	4.5120	**R17**	0.3438	4.5120	**R2 2**	0.53	4.9772
R 3	0.3438	13.1240	**R8**	0.3438	4.5120	**R1 3**	0.3600	4.6080	**R18**	0.3438	4.5120	**R2 3**	0.44	4.9476

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R4	0.34 38	13.12 40	**R9**	0.34 38	4.512 0	**R14**	0.34 38	4.5120	**R19**	0.36 00	4.60 80	**R24**	0.44 13	4.93 11	
R5	0.34 38	13.12 40	**R10**	0.36 00	4.60 80	**R15**	0.36 00	4.60 80	**R20**	0.34 38	4.512 0	**R25**	0.46 63	4.97 73	

Defuzzification

The final process is a process known as the defuzzification process, which is the process of finding out the output value in the form of crisp (z) value. The method used here is the Center Average Defuzzifier.

$$Z = \frac{\Sigma \alpha i \, zi}{\Sigma \alpha i} \quad \text{..... (4)}$$

in which:

Z: Output variables

α_p: α predicate value

z_i: Output variables value

$$Z = \frac{115{,}5806}{9{,}3047} = 12.4217$$

From this equation, the results obtained are as listed in Table 7 below.

Table 7. Output Distance from Fuzzy Calculation

No	Result (K6)	Range
1	Re-learn	0 ≤ N < 12.42
2	Passed	12.42 ≤ N ≤ 20

So, the minimum standard score per category used is 12.42. The results of the fuzzy calculations are then used as a passing standard as can be seen in table 8 below which presents examples of the scores of five participants.

Table 8. Participants Grade Result per Criteria (example of five participants)

Criteria	ID 1		ID 2		ID 4		ID 17		ID 18	
	Scr	Result	Scr	Result	Scr	Result	Scr	Result	Scr	Result
K1 (Listening)	9.5	Re-learn	12.5	Passed	13	Passed	11	Re-learn	15.5	Passed
K2 (Reading)	10	Re-learn	6.5	Re-learn	13.5	Passed	12	Re-learn	15	Passed
K3 (Grammar)	4.5	Re-learn	7	Re-learn	11	Re-learn	12	Re-learn	11	Re-learn

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K4 (Social Skills)	11	Re-learn	13.5	Passed	12.5	Passed	14	Passed	16	Passed
K5 (Picture)	10.5	Re-learn	13	Passed	15	Passed	15.5	Passed	11	Re-learn

Based on the table above, Participant with ID 1 must repeat all categories because all scores in the categories are below the passing threshold (minimum score result). Participant ID2 passed in three categories (K1, K4, and K5) but had to repeat in the other two categories (K2 and K3). Participant ID 4 passed in four categories (K1, K2, K4, and K5) and only had to repeat in one category (K3). Participant ID 17 repeated in three categories (K1-K3) and passed in two categories (K4 and K5). Participant ID 18 also passed three categories (K1, K2, and K4) and had to repeat in two categories (K3 and K5).

From the results per category, there is still a quite disturbing problem, i.e., participants with a composition of three passes and two re-learn, or even vice versa. Because with the level of points and three levels of difficulty of questions, participants with three passed categories may have to re-learn in the overall scoring, while participants who only get two passed categories will be included in the passed category in the overall scoring.

Overall Fuzzification

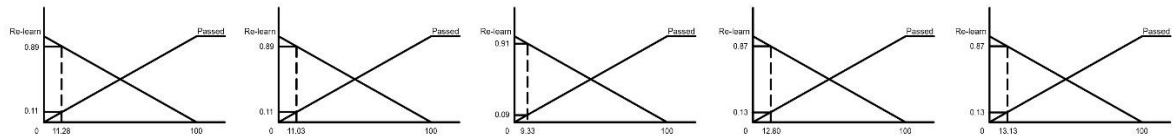
This calculation measures the score results from all questions (50 questions). The value range used is 0-100, so the minimum score result cannot be relied on the calculation results per category. The value range used is still the same as the calculation per category (Table 3) but with different minimum and maximum values. Fuzzification calculations on the data above use a formula with results as below:

$$Re-learn\ (x) = \begin{cases} 1; & x \leq 100 \\ \frac{(100-x)}{(100-0)} & 0 \leq x \leq 100 \\ 0; & x \geq 0 \end{cases} \quad \text{..... (5)}$$

$$Passed\ (x) = \begin{cases} 0; & x \leq 100 \\ \frac{(x-100)}{(100-0)} & 0 \leq x \leq 100 \\ 1; & x \geq 0 \end{cases} \quad \text{..... (6)}$$

Table 9. Overall Fuzzification Results

Result	K1	K2	K3	K4	K5
μRe-learn (x)	0.8873	0.8898	0.9068	0.8720	0.8688
μPassed (x)	0.1128	0.1103	0.0933	0.1280	0.1313



K1 **K2** **K3** **K4** **K5**

Figure 2. Fuzzification Diagram of *Overall Result*

Fuzzy Inference for Overall Result

The rules used are still the same as in the calculations per category (Table 6), namely with 5^2 rules making it twenty-five rules. In finding the α value, it is necessary to find intersections between categories in one rule, as in the example of the rule formula (R1) below:

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R1: If L **Re-learn** and R **Re-learn** and G **Re-learn** and S **Re-learn** and P **Re-learn** then **Re-learn.**

α1 = μL Re-learn [X] ∩ R Re-learn [X] ∩ G Re-learn [X] ∩ S Re-learn [X] ∩ Re-learn [X]

= min (μ[0.8883] [11.18] ∩ [0.8898] [11.03] ∩ [0.906] [9.33] ∩ [0.872] [12.8] ∩ [0.8688] [13.13])

= 0.8688

Meanwhile, the calculation of the Z value (ex. Z1 calculation) is done using the formula below:

Z1 = Zmax – α1 (Zmax – Zmin)

Z1 = 100 – 0,8688 (100-0)

Z1 = 100 – 86,88

Z1 = 13.12

The results of calculating α and Z to get the Overall Minimum Score Results for the twenty-five rules are in table 10 below.

Table 10. *Overall Rule Base Results*

R	α_p	Z	R	α_p	Z	R	α_p	Z	R	α_p	Z	R	α_p	Z
R1	0.8688	13.12	**R6**	0.1313	86.87	**R11**	0.0933	90.67	**R16**	0.128	87.2	**R21**	0.0933	90.67
R2	0.1118	88.82	**R7**	0.1103	88.97	**R12**	0.08	92	**R17**	0.0933	90.67	**R22**	0.1103	88.97
R3	0.1103	88.97	**R8**	0.0933	90.67	**R13**	0.1103	88.97	**R18**	0.8688	13.12	**R23**	0.0933	90.67
R4	0.0933	90.67	**R9**	0.1118	88.82	**R14**	0.0933	90.67	**R19**	0.1103	88.97	**R24**	0.0933	90.67
R5	0.128	87.2	**R10**	0.1118	88.82	**R15**	0.0933	90.67	**R20**	0.0933	90.67	**R25**	0.0933	90.67

Defuzzification for Overall Result

The final process is a process known as the defuzzification process, the process of finding out the output value in the form of crisp (z) value. The method used here is the Center Average Defuzzifier.

$$Z = \frac{235,7983}{4,1181} = 57.2590$$

From this equation, the results obtained are as listed in Table 11 below.

Table 11. Output Distance of Fuzzy Result

No	Result (K6)	Range
1	Re-learn	0 ≤ N < 57.25
2	Passed	57.25 ≤ N ≤ 100

So, the minimum standard overall score used is 57.25. The overall minimum standard results (output distance) are then compared with the original data calculations (sub-total score) to obtain results (Overall Result) as in the example below.

Table 12. Participants Grade Result per Criteria and Overall (example of five participants)

Criteria	ID 1		ID 2		ID 4		ID 17		ID 18	
	Scr	Result	Scr	Result	Scr	Result	Scr	Result	Scr	Result
K1 (Listening)	9.5	Re-learn	12.5	Passed	13	Passed	11	Re-learn	15.5	Passed

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K2 (Reading)	10	Re-learn	6.5	Re-learn	13.5	Passed	12	Re-learn	15	Passed
K3 (Grammar)	4.5	Re-learn	7	Re-learn	11	Re-learn	12	Re-learn	11	Re-learn
K4 (Social Skills)	11	Re-learn	13.5	Passed	12.5	Passed	14	Passed	16	Passed
K5 (Picture)	10.5	Re-learn	13	Passed	15	Passed	15.5	Passed	11	Re-learn
Score sub-total	45,5		52.5		65		64,5		68,5	
Output Distance	57.25		57.25		57.25		57.25		57.25	
	45,5 < 57.25		52.5 < 57.25		65 > 57.25		64,5 > 57.25		68.5 > 57.25	
Overall Result	**Re-learn**		**Re-learn**		**Passed**		**Passed**		**Passed**	

Based on the calculation results above, Participant with ID 1 must repeat (re-learn) all categories. From the overall score results, participant ID 2 must repeat (re-learn) even though he/she was passed in three categories (K1, K4, and K5). Participants with ID 4 are considered to have passed and have the option of repeating (re-learn) the material/category of grammar only. Participant ID 17 is also considered to have passed even though he only passed in two categories and had to repeat in three categories. Meanwhile, unlike participant ID 2, participants with ID 18 are overall considered to have passed even though they also passed in three categories. The overall conclusion of the results is as follows:

Table 13. Participants Grade Result (*Passed and Re-learn*)

Kriteria	Passed	Re-Learn	Total
Listening	9	11	20
Reading	8	12	20
Grammar	6	14	20
Social Skill	12	8	20
Picture	13	7	20
	48	52	100
	48%	**52%**	

Mean Absolute

The two minimum score report calculation results above are then calculated using the Mean Absolute Percentage Error (MAPE) formula, resulting in a MAPE value of 7.92% for calculations per category and 0.51% for overall. The correctness value of this calculation reached 92.08% for per category and 99.49% for overall. The calculation is as follows:

Table 14. MAPE Calculation (Per Category and *Overall*)

Student Score	Result per Category	Result Overall
r Actual Score	11.51	57.55
Fuzzy Tsukamoto Calculation	12.42	57.26
MAPE	7.92%	0.51%
Accuracy	**92.08%**	**99.49%**

With this method all participants who still have re-learn results in their assessment category, still must repeat. The learning process will take place with structured scheduling, where participants will only enter sessions where they repeat.

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CONCLUSION

From the five examples of calculating the overall score above (table 14), passing in three of the five categories is not enough, because in overall, it may still be considered that the participant is still has to re-learn. This provides at least 2 benefits for teachers/tutors and participants, i.e.: 1) being able to know the mapping of participants' abilities so they can prepare learning plans well, and 2) being able to know participants' strengths and weaknesses so they can focus on improving their weaknesses and developing their strengths. In terms of calculations using fuzzy Tsukamoto, the results of the minimum score report obtained, both per category and overall, were then calculated using the Mean Absolute Percentage Error (MAPE) formula and obtained a truth value of 92.08% for calculations per category, and 99.49% for overall calculation. These results show that calculations using fuzzy Tsukamoto have fully accurate results because the MAPE value is ≤ 10.

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