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Intelligent Tutoring System for Identification of Learning Styles and Assignment Educational Strategies

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Abstract. The possibility of improving the learning that a student obtains considering the learning styles that he or she has, refers to the best way to retain learning based on 4 primary stimuli, such as sight, hearing, touch, and experience. In this research work, an intelligent tutoring system is described based on 2 small surveys. The system will obtain sufficient information to determine those educational strategies or techniques that favor not only the students as individuals but the classroom as a group, also favoring the teacher a route learning process focused on how students learn best. To obtain educational strategies, the intelligent tutor system makes use of one of the multiple techniques of artificial intelligence such as fuzzy logic, necessary to obtain a result with greater precision, an issue that would hardly be possible using basic logic or conventional due to the uncertainty it generates. In turn, the software is developed using the Laravel work environment using MySQL as the main database manager.
Keywords: Fuzzy logic, artificial intelligence, tutor system.

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1 Introduction

The words artificial intelligence or intelligent tutor system (ITS) intuitively tend to relate these concepts to new technologies in development. In 1970 Carbonell gave the initiative to apply Artificial Intelligence techniques to Computer Aided Instruction (CAI) systems; He is credited with the creation of the first Intelligent Tutor: The Scholar (an intelligent tutor for teaching the geography of South America), although the term “Intelligent Tutor System” is later defined by Wolf (Correa, 2014).

Wolf in 1984 defined ITSs as systems that adjust the teaching, learning, communication and retention of the teacher's knowledge and the student's reasoning about that knowledge, which means that the primary objective of all STIs is to facilitate the work of the teaching-learning process always considering the extent of its computational possibilities (Wolf, 1984).

Nowadays, in basic and upper secondary education, it is essential to effectively transmit the expected information, considering the multiple learning styles that students may present. In a basic education school located in Reynosa Tamaulipas (Mexico), within the third-grade group there are considerable percentages in terms of average achievement of students within specific areas of knowledge.

This article proposes the innovation of an ITS by implementing artificial intelligence techniques such as fuzzy logic based on the learning styles of the VARK method to obtain educational strategies that allow for a more accurate result. As well as the monitoring that the system will carry out together with the teacher, providing quarterly reports on the group's performance, with the purpose of directly influencing the development of the classes, with which a better absorption of knowledge is expected, as well as an increase in student grades.

2 Theoretical foundations

2.1 VARK questionnaire

The tool used by Fleming to measure how much ability an individual has within the learning styles that the VARK model has is known as the VARK questionnaire. In 2006, Fleming restructured the VARK questionnaire with the aim of making it more precise and reliable. As a result, a total of 16 questions were obtained with a total of 4 answers per question, each of the answers referring to one of the learning styles (Visual, Auditory, Reading Writing, Kinesthetic) (Fleming & Mills, 2019).

Through this questionnaire, the aim is to determine the learning styles of the group and make the teacher aware of the results obtained, in this way the teacher will have the possibility of being able to address the topics trying to apply the learning styles that the group needs for a greater exploitation.

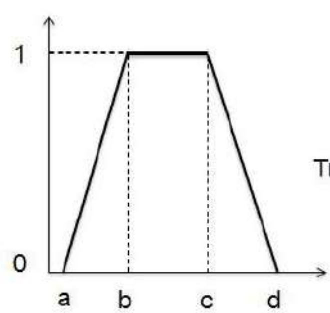
2.2 Diffuse logic

Fuzzy logic is a branch of artificial intelligence, Artificial Intelligence (AI) can be defined as An area of computing that deals with symbols and non-algorithmic methods for solving problems (Ponce Cruz, 2010).

To understand the concept of fuzzy logic it is necessary to understand the different concepts that exist about logic itself, Logic is established as the study of the conditions of truth (Lefebvre, 1970).

Fuzzy logic will never handle only two states (true or false), but rather a set of values between 0 and 1. Thanks to the use of fuzzy sets, it is possible to know the degree of membership that an individual has to the set. as such, an element may or may not belong to the set. However, the element can belong to a specific degree that is in the range {0,1}. The degree to which an element "x" belongs to the set A is denoted as not µ_A(x). Therefore, if "x" does not belong to the set A, it is denoted as µ_A(x) = 0, while if µ_A(x)= 1 it will mean that "x" completely belongs to the set A. A value µ_A(x) = 0.2 indicates that "x" has a low degree of belonging to set A while micro µ_A(x)= 0.9 indicates a high degree of belonging (García Serrano, 2016).

To obtain the degree of belonging (Iglesia Feria, 2016) that an element has within the set, it is necessary to use a belonging function and its reference graph. There are multiple techniques, but the one used in this project is the trapezoidal one, which must be one of the most used. Figure 1 shows the general scheme for trapezoidal graphs.



$$\text{Trapezoidal}(X, a, b, c, d) = \begin{cases} 0 & X \leq a \\ \dfrac{X-a}{b-a} & a \leq X \leq b \\ 1 & b \leq X \leq c \\ \dfrac{d-X}{d-c} & c \leq X \leq d \\ 0 & d \leq X \end{cases}$$

Figure 1. Trapezoidal graph

As can be seen in Figure 1, a crescent is obtained that goes from point "a" to point "b", this is used in order to reduce the uncertainty that exists when going directly from a state of denial to one of affirmation. , subsequently from point "b" to point "c", a stable line is maintained which indicates the range of values where the degree of belonging would always be 1, and then decreases to a point "d", to the values between the point "a" and point "d" and their respective degrees of truth are known as the universe of discourse. Therefore, the belonging function (listed with 5 equations on the right side of figure 1) would be interpreted in the following ways:

1) For any input value (x) less than or equal to "a" the result will be a degree of membership of 0.0

2) For any input value greater than or equal to “a” and less than or equal to “b”, the result will be the difference between the subtraction of the input value minus point “a”, and the subtraction of the value of point “b” minus the value of point “a”, this degree of belonging must belong to a range between 0 and 1.
3) For any input value greater than or equal to “b” and less than or equal to “c” a belonging degree of 1.0 will be obtained as a result.
4) For any input value greater than or equal to “c” and less than or equal to “d”, the result will be the difference between the subtraction of point “d” minus the input value, and the subtraction of the value of point “d” minus the value of point “c”, this degree of belonging must belong to a range between 0 and 1.
5) For any input value (x) greater than or equal to “d” the result will be a degree of belonging of 0.0.

2.3 Fuzzy Inference Process

The fuzzy inference process is expressed through the following stages: 1) Input data 2) Fusific. First stage Input data: it will largely depend on how the mathematical problem to be solved is posed. For optimal fuzzy logic work, it is recommended to use at least 2 variables. Second stage Fusific: it is a mathematical procedure in which an element of the universe of discourse is converted into a value in each belonging function to which it belongs (UDEP, 2020). Third stage evaluation of fuzzy rules: Fuzzy rules are propositions that allow expressing the knowledge available about the relationship between antecedents and consequents. To express this knowledge completely, several rules are normally required, which are grouped together forming what is known as a rule base. The edition of this base determines what the behavior of the fuzzy controller will be. Fourth stage inference: There are many methods, for example: mandani minimum inference, Larsen product inference, Drastic product inference and Bounded product inference. Fifth aggregate stage: consists of agglomerating the fuzzy sets resulting from the evaluation of the fuzzy rules necessary for the defuzzification stage. Sixth stage “defuzzification”: A mathematical process used to transform a fuzzy set into a real numerical entity (UDEP, 2020).

3 Methodology

3.1 Linguistic Variables

The linguistic variables or performance groups provided by the Early Warning System (SisAT) implemented by the Secretary of Public Education (SEP) of Mexico (SEP, 2013), which are included in a range of requires support, in development and expected level, this in order to adapt the classes not only to the predominant learning style of the individual and therefore in the group, but also to take into consideration their performance throughout the course to adjust the level of difficulty of the class strategies to provide.

3.2 Modeling of Input Variables

To model the input variables, a range of values must be delimited for each of them. Learning styles can prevail between a range of 0 to 16 according to the VARK questionnaire, which results in the following relationship: A rating of 0 to 6 points is considered a low mastery of the learning style. A score of 5 to 11 points is considered an average mastery of the learning style. A score of 10 to 16 points is considered high mastery of the learning style. The purpose of superimposing the values of the ranges is to reduce the degree of uncertainty that would be caused by moving from one state to another in a non-progressive manner. The modeling of the linguistic variables is already pre-established in advance, referring to the performance demonstrated by the student, so based on this it is found that: A grade of 5 to 7 is considered Requires support. A score of 6.5 to 8 is considered Developing. A rating of 7.5 to 10 is considered Expected.

3.3 Output Variable Modeling

As an output variable, a student will be declared within one of the three groups of activities proposed for his or her learning style, with group 1 being the one that contains the most complex activities and group 3 being the one that contains the simplest activities. This is to adapt class planning not only to the learning style but also to its performance. The strategies proposed to be used for each learning style are the following: Visual (diagrams, graphs, colors, tables, written texts, different types of letters, different spatial arrangements), Auditory (debates, discussions, conversations, audios, videos, seminars, music), Reader-writers (books, readings, written feedback, note taking, essays, multiple choice, bibliographies) and Kinesthetics (Examples from daily life, lectures, demonstrations, physical activity, constructions, role-playing, work models). Once the student answers the VARK questionnaire, they will already have one or more learning styles established as predominant. They will then be asked to determine from 1 to 7 the level of difficulty that each strategy has according to their learning style(s). In this way, those activities that most frequently have ratings of 1 and 2 will correspond to group 1, activities with ratings of 3,4 and 5 will be classified in group 2, and finally, group 3 will contain the activities with ratings of 6 and 7.

3.4 Fuzzy Rules and Defuzzification Process

The fuzzy rules that will govern the entire fuzzy process are declared through the relationship between these 2 input variables and our output variable, as shown in Table 1.

Table 1. Graphic model of the fuzzy rules.

	Requires Support	In development	Expected
Low	Group 3	Group 3	Group 2
Half	Group 3	Group 2	Group 1
High	Group 2	Group 1	Group 1

In table 1 the following fuzzy rules are interpreted: If Performance is equal to Requires Support and Learning Style is equal to Medium or Low then Activities is equal to Group 3. If Performance is equal to Requires Support and Learning Style equals High then Activities equals Group 2. If Performance equals In development and Learning Style equals Low then Activities equals Group 3. If Performance equals In development and Learning Style equals Medium then Activities equals Group 2. If Performance equals In development and Learning Style equals High then Activities equals Group 1. If Performance equals Expected and Learning Style equals Low then Activities equals Group 2. If Performance equals Expected and Learning Style equals Medium or High then Activities is equal to Group 1. With the use of these 7 rules, the group to which each student must belong will be determined in a more appropriate way, for the defuzzification process which will indicate the exact point to which the student is related.

3.5 Selection of Learning Styles Model and Evaluation Method

To select the appropriate model, the following aspects are taken into consideration in hierarchical order based on the needs of this project.

- The model must be fully adaptable to the pedagogical field.
- The model must have a balanced number of stimuli so that the teacher's workload does not increase greatly.
- The stimuli must be capable of being controllable by the strategies to be implemented by the teacher.

The VARK model is the optimal one to work to meet these 3 requirements and at the same time use stimuli that students have been using consciously for at least 8 educational levels. Furthermore, this questionnaire is used since it is the one that best adapts to the age of the students, and at the same time its estimated completion time is no more than 15 minutes, also having the benefit that the time for analyzing results through a system Intelligent tutoring would have the answer to this evaluation immediately and no human interpretation would be needed to achieve it.

3.6 Selection of Learning Strategies

Within the VARK model there are four major stimuli: visual, auditory, reading-writing, and kinesthetic. The next step in the procedure is to evaluate suitable strategies for each of these stimuli, thus achieving a repository of learning strategies (or techniques). For each learning style, the following strategies are available (González, Alonso & Rangel, 2012):

- Visuals: Diagrams, graphs, colors, tables, written texts, different fonts, and different spatial arrangements.
- Auditory: debates, discussions, conversations, audios, videos, seminars, and music.
- Reader-writers: books, readings, feedback, note taking, essays, multiple choice, and bibliographies.
- Kinesthetics: real-life examples, guest lectures, demonstrations, physical activity, constructions, role-plays, and working models.

3.7 ITS Structure and Artificial Intelligence Technique

The ITS must have a series of modules. To facilitate the development of the ITS structure, the proposal by Carbonell (Ferreira & Kotz, 2012) will be used. This structure divides the system into three large modules: the domain module, the teacher module, and the student module, these being connected to an interface. graphic where users according to their role will have an interaction with the system. This structure is used due to the rapport it has with a web development system, which is where the intelligent tutor will be integrated. For a tutor system to be considered intelligent, it must have some technique or branch of artificial intelligence, as its name suggests. For this reason, fuzzy logic is used as a means of evaluating questionnaires due to its practicality in the evaluation of linguistic variables and the advantage of not having uncertainty. Furthermore, the attributes of the students will be used not probabilistically, but through degrees of truth, that is, it is not evaluated how likely it is that a student has or does not have a learning style, but rather the amount of mastery that a student has. student about each learning style.

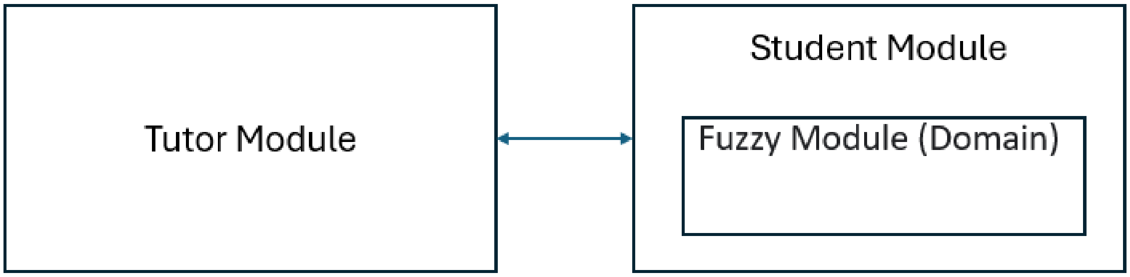


Figure 2. Modules of the Intelligent Tutor System

Data Collection: The input variables are collected directly from the student module and the Tutor module, this being the grade obtained in the learning styles questionnaire and the development index of the current school year.

Fusification of the learning style domain: To calculate the degree of truth of the first input variable, it is necessary to consider that it must be calculated for each of the domains (low, medium, high). For each domain the following conditionals are followed:

- For a Low domain, if the score obtained is less than or equal to 5, it will have a degree of truth equal to 1, while any score greater than or equal to 6 will obtain a degree of truth equal to 0.
- For a Medium domain, a degree of truth equal to 1 will only be obtained when the score is greater than or equal to 6 and less than or equal to 10.
- For a High domain, a degree of truth equal to 1 will only be granted if the score obtained is greater than or equal to 11.

Performance Index Fusification

In the same way as the previous variable, it is necessary to calculate the degree of truth for each performance group, which are: Requires support, In development and Expected. For each development the following indications are used:

- For a performance Requires Support, if the index is greater than or equal to 7 the degree of truth is equal to 0, for any index less than or equal to 6.5 the degree of truth will be 1, in case the index is in a range between 6.6 and 6.9, equation (1) is used, with "x" being the performance index:

$$\mu Low = (6 - x) / (6 - 5) \quad (1)$$

- For a performance In development, the 3 possible ranges must be identified, if it belongs to a range between 6.5 and 7, equation (1) is used, otherwise if the value of the index is between 7 and 7.5, a grade is obtained. of truth equal to 1. Finally, if the index belongs to a range between 7.5 and 8, equation (2) will be used to obtain the degree of truth.

$$\mu Development = (x - 5) / (6 - 5)$$
$$\mu Development = (11 - x) / (11 - 10) \quad (2)$$

- For an Expected performance, for a performance index greater than or equal to 8 the degree of truth is equal to 1, in case the index belongs to a range between 7.5 and 8, equation (3) must be used to obtain the degree of truth.

$$\mu Development = (x - 10) / (11 - 10) \quad (3)$$

Application of Fuzzy Rules: A set of 3 groups of fuzzy rules is used that govern the behavior of the data within the system, these being the following:

$$\mu group3\_1 = \min(\mu Support, \mu Low)$$
$$\mu group3\_2 = \min(\mu Support, \mu Half)$$
$$\mu group3\_3 = \min(\mu Development, \mu Low)$$
$$\mu group2\_1 = \min(\mu Support, \mu High)$$
$$\mu group2\_2 = \min(\mu Development, \mu Half)$$

μgroup2_3 = min(μExpected, μLow)
μgroup1_1 = min(μDevelopment, μHigh)
μgroup1_2 = min(μExpected, μHalf)
μgrupo1_3 = min(μExpected, μHigh)
Fuzzy Rule Groups

Aggregation: Once the rules have been evaluated using the min function which returns the minimum value within all the parameters provided, it is essential to obtain the degree of truth for each group of learning style strategies, for this the following 3 equations are used, respecting the max function which returns the largest value of all the parameters entered:

$$\mu group1 = \max(\mu group1\_1, \mu group1\_2, \mu group1\_3) \tag{4}$$
$$\mu group2 = \max(\mu group2\_1, \mu group2\_2, \mu group2\_3) \tag{5}$$
$$\mu group3 = \max(\mu group3\_1, \mu group3\_2, \mu group3\_3) \tag{6}$$

Defuzzification: To develop the defuzzification process, it is required to delimit the universe of discourse for each group of membership. The new upper limit will be established by the degree of truth obtained in the previous step. Once this is established, we proceed to evaluate equation (7):

$$\text{Belonging group} = \sum Xi\ \mu(Xi) / \sum \mu(Xi) \tag{7}$$

The formula establishes that the sum of the multiplication of each value of the universe of discourse by its respective degree of truth must be carried out and divided by the sum of the degrees of truth, because the formula will not yield a specific integer, The following conditions must be followed for the assignment of belonging:

- The student will belong to strategy group 1 when the dependent variable returns a value less than or equal to 1.6.
- The student will belong to strategy group 2 when the dependent variable returns a value less than or equal to 2.3 but greater than or equal to 1.7.
- The student will belong to strategy group 1 when the dependent variable returns a value greater than or equal to 2.4.

Assignment of Strategies by Group: For the order of assignment of the strategies, quartiles are used, making the adaptation of using only 3 groups instead of four as is commonly established. In this case, what is sought is to find the strategies that are in the second quartile, therefore which proceeds to sort the numerical values in ascending order (N1,…, N7).

Next, it is necessary to calculate the lower limit and the upper limit for each group of strategies; this is done by obtaining the first quartile and the second quartile. To obtain the quartiles, equation (8) is used, with k being the number of quartiles to be searched and N being the amount of existing data.

$$Qk = (k*N) / 3 \tag{8}$$

Once the quartile limits are obtained, the range of scores will be established for each of the strategies, thus managing the strategies belonging to each student. Once the individual reports have been generated, the general report will be updated in real time each time a student successfully completes this stage, resulting in the most present learning styles and the most recommended strategies per group. Figure 3 expresses the diffuse process in greater detail.

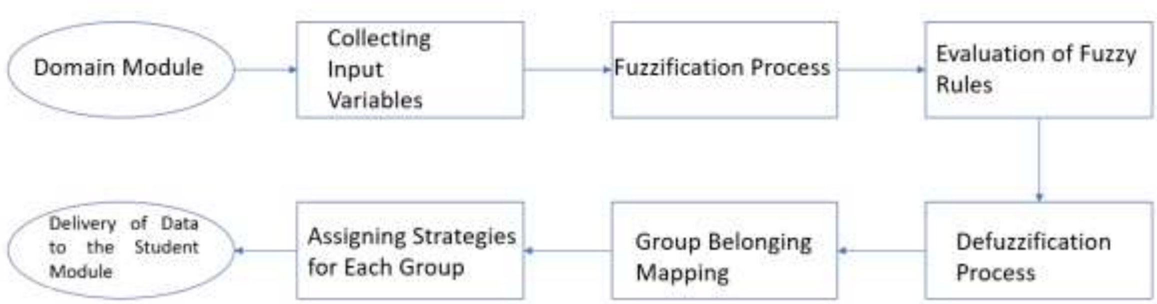


Figure 3. Domain Module Flowchart.

3 Experimentation

3.1 Sampling Unit

The sampling unit for this research consists of 3rd year students group "A" in the subject of technology as a non-probabilistic sample, there is a total of 14 students who addressed the experimental stage of the system, for confidentiality reasons and to maintain the anonymity of the students, pseudonyms will be used since none of these students is of legal age.

3.2 Independent Variables

The independent variables presented by the system are 2, the development index provided by the early warning system platform which varies in a range of 5.1 to 10 and the learning style domain obtained through the VARK questionnaire within the student's module. All 14 students had the following developmental indices (Table 2).

Table 2. Ratio of students to their developmental index.

Student	Development Index
1	6
2	9.3
3	10
4	8.6
5	10
6	7.6
7	9.6
8	10
9	10
10	7
11	9.6
12	5.6
13	8
14	10

Once the learning styles questionnaire has been answered, the student is assigned one or more styles depending on the score achieved within the questionnaire (Table 3). For example, if a student does not have a range of difference greater than 2 points over the maximum score and one of the other scores, these styles will also be considered dominant. As can be seen in Table 3, student 10 has a mastery of 10 points over the reading and writing learning style, considering the previous rule, any style with a score greater than or equal to 8 will also be considered as dominant, to maintain as much information as possible.

Table 3. Relationship of students with their score obtained in the learning styles questionnaire.

Student	Visual	Auditory	Reading and Writing	Kinesthetic
1	8	6	3	9
2	4	6	5	6
3	8	10	6	8
4	1	5	8	2
5	3	4	2	8
6	2	7	3	5
7	9	9	12	7
8	7	5	9	12
9	3	11	9	4
10	8	4	10	7
11	4	3	4	5
12	5	4	5	9
13	5	6	6	7
14	6	4	3	3

3.3 Fuzzy Process

Once the two input variables have been established, it is necessary to highlight that the following fuzzy process must be repeated as many times, as well as the number of learning styles that the student has, ignoring that the independent variable referring to the learning style will be different in each of these cases since each learning style has its own score.

3.4 Fuzzification of the Learning Styles Domain

Referring to the auditory learning style, it has a score of 7 for this specific student, in turn the development index has a score of 7.6, which broadly categorizes the student in a medium domain. and performance at the requires support level. To adjust these variables in a fuzzy process, it is necessary to collect the degree of truth that each domain group has: Low (Fig. 4), Half (Fig. 5) and High (Fig. 6).

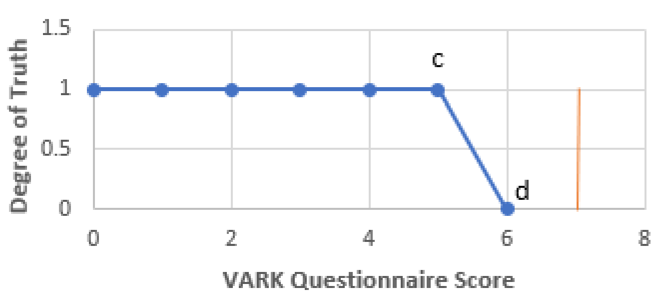


Figure 4. Fuzzy graph expressed in degrees of truth for a low learning style domain.

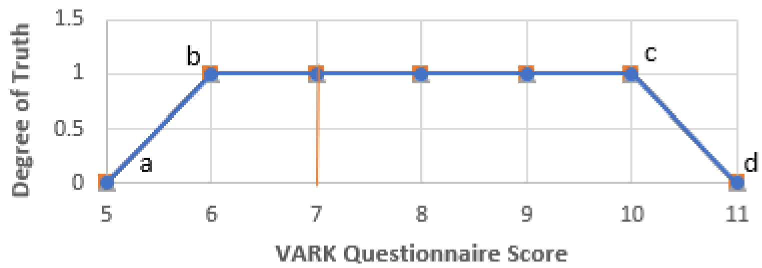


Figure 5. Fuzzy graph expressed in degrees of truth for a medium learning style domain.

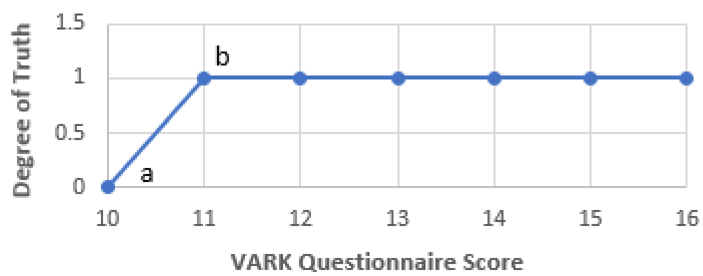


Figure 6. Fuzzy graph expressed in degrees of truth for a high learning style domain.

As seen in Fig. 4, 5 and 6, the score obtained in the learning style questionnaire places the student in an average domain, thus granting the following degrees of truth for each of the domains:

$$\mu Low = 0 \qquad \mu Half = 1 \qquad \mu High = 0$$

3.5 Fusification of the Performance Index

The process for fusing the development indices is the same simply using different parameters, it is necessary to calculate the degrees of truth for each of the 3 performance groups Requires Support (Fig. 7), In Development (Fig. 8), Expected (Fig. 9). For this experimentation and continuing with what was outlined in the previous section, the student manages a development index of 7.6.

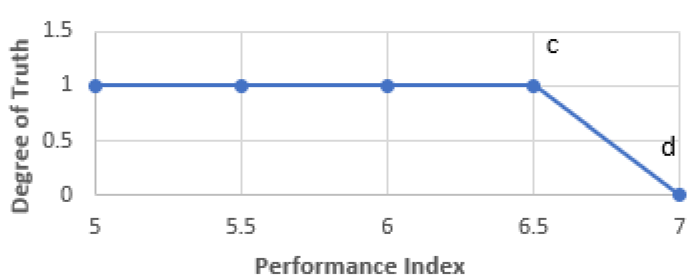


Fig. 7. Fuzzy graph expressed in degrees of truth for a performance where the student requires support.

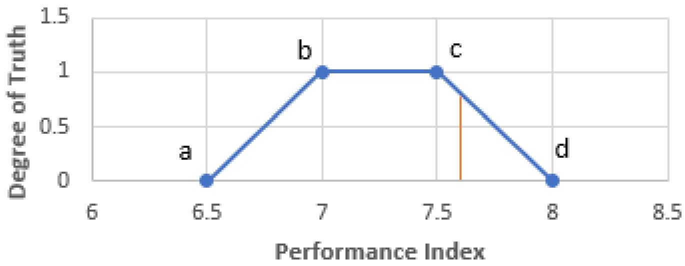


Figure 8. Fuzzy graph expressed in degrees of truth for a performance where the student is in full development.

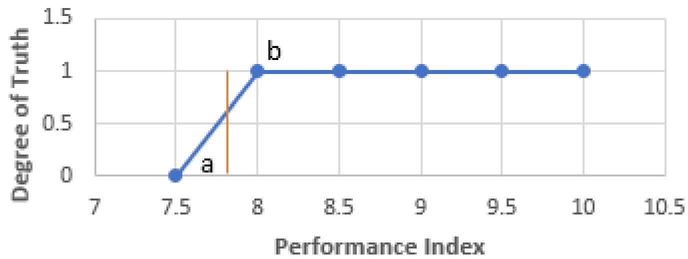


Figure 9. Fuzzy graph expressed in degrees of truth for a performance where the student is at an expected level.

As seen in figure 7, 8 and 9, the development index falls within the discourse universe of the In Development and Expected performances, which is why the following results are obtained:

µSupport= 0 µDevelopment = 0.8 µExpected = 0.2

3.6 Evaluation of Fuzzy Rules

Once the fuzzy rules have been established, we proceed to substitute the degrees of truth obtained in the fusification process, thus applying the min function, which refers to obtaining the smallest number among all the parameters provided, as a result we obtain the degrees of truth for each formula, below are those whose degree of truth was different from 0:

µgroup2_2 = 0.8
µgroup1_2 = 0.2

The last step consists of applying a max function to the subset of rules to obtain the degree of truth belonging to each group of learning strategies which refers to the dependent variable.

µgroup1 = 0 µgroup2 = 0.8 µgroup3=0.2

3.7 Aggregation and Defuzzification

Once the degrees of truth for the dependent variable have been obtained, it is time to adjust its universe of discourse, resulting in this, the new upper limit for group 1 is equal to 0, for group 2 it is equal to 0.8 and for group 3 it is equal to 0.2 (Fig. 10).

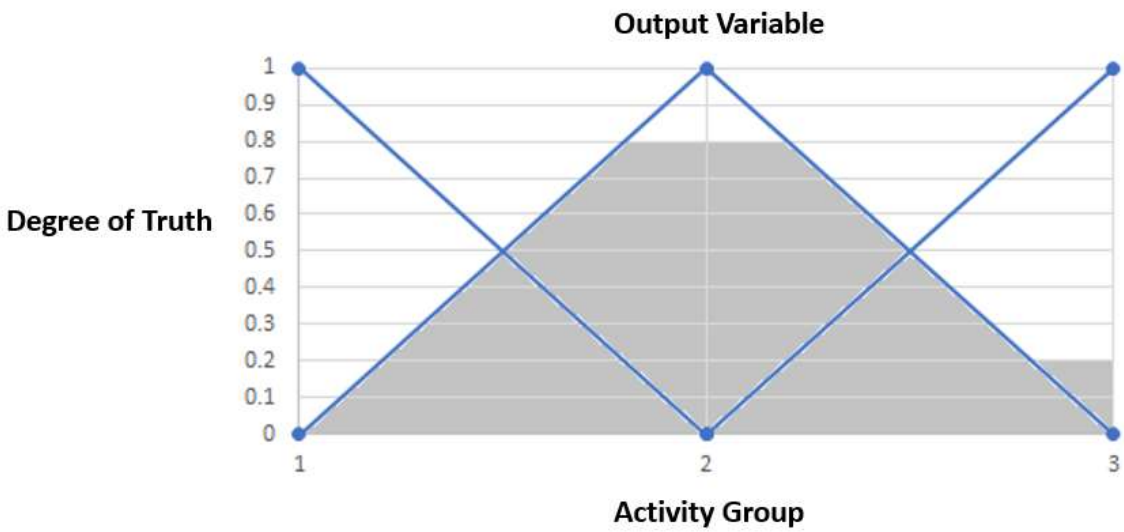


Figure 10. Fuzzy graph expressed in degrees of truth for the output variable.

The remaining step is to find for each point on the graph its respective degree of truth, for this the following equation results:

$$\text{Belonging group} = (1 * 0 + 2 * 0.8 + 3 * 0.2)/(0.8+0.2) \quad (9)$$

This indicates that the student in question for the auditory learning style belongs to group 2.2, however, the existing and available groups are 1, 2 or 3. Based on the rounding criteria established previously, the student is assigned assigns group 2 of listening strategies.

3.8 Selection of Learning Strategies by Group

Nested in the learning styles questionnaire, the student is asked to assign a level of difficulty for each strategy to be used, due to the need to not only adjust the strategies to the learning style but also make sure to assign only those that are possible for them to carry out. For this experiment, student 6 assigned the scores shown in table 3 to the listening strategies:

Table 4. Score given by student 6.

Strategy	**Score**
Debates	7
Discussions	5
Conversations	8
Audios	9
Videos	9
Seminars	4
Music	9

According to Table 4, the result is 5.33 for the first quartile and 8.66 for the second quartile. Due to this, this particular student will be assigned strategies that have a score greater than or equal to 5.33 but less than or equal to 8.66, resulting in the Debates and Conversations strategies belonging to this student, for this specific learning style.

4 Results

Of the 14 students surveyed, it was found that 9 of them had mastery over the kinesthetic learning style, mentioning again that a student can have at least one of the learning styles, but a student can also present up to 4 learning styles. of the VARK model, for this reason Fig. 11 represents the number of students who presented said learning style, having a tie in the visual, auditory, and reading styles with a score of 7 points.

Figure 11. Learning Styles present by Student.

Once all the learning techniques or strategies were corroborated, the following results were obtained for each learning style. For visual techniques, it was identified that it is more suitable for students to use colorful designs, with diversity in font size in the presentations; as well as the use of graphics to demonstrate the topics. In Fig. 12 you can see the number of students in whom each of the techniques for the visual learning style predominates.

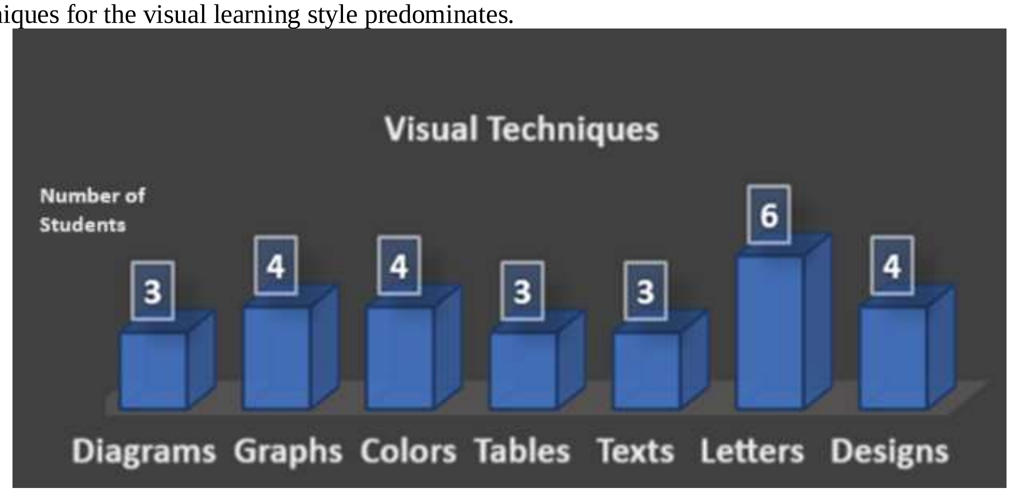


Figure 12. Visual Techniques present by Student.

For auditory techniques, there is a greater predisposition towards the use of background music when taking exams or long tasks, thus supporting the concentration of students. The ITS also identified that seminars are the optimal tool for students. In Fig. 13 you can see the number of students in whom each of the techniques for the auditory learning style predominates.

Figure 13. Listening Techniques present by Student.

In reading-writing techniques, it is observed that the techniques or strategies are not very different from each other, what can be referenced is that multiple-choice exams do not favor the majority of students, which is why learning benefits from the use of readings, note taking, essays and written feedback, in Fig. 14 you can see the number of students in whom each of the techniques for the reading-writing learning style predominates.

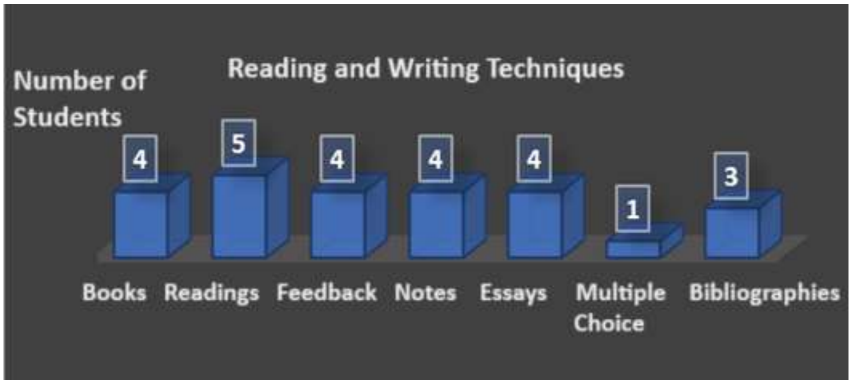


Figure 14. Reading-writing techniques present by student.

Finally, the kinesthetic style was the one that was presented in the majority of the students (60% of them), a greater difference was found in the techniques assigned to the students, using physical activity through play to enhance learning retention, as well as the invitation of professors to present topics from their area of application. In Fig. 15 you can see the number of students in whom each of the techniques for the kinesthetic learning style predominates.

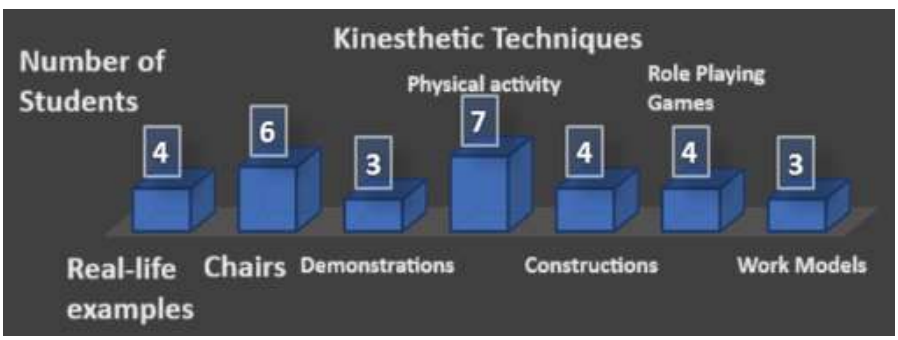


Figure 15. Visual Techniques presented by Student.

Applied the relevant techniques of learning styles within the formulation of the exams, as well as the teaching material to teach classes in the development of the second and third quarter in the months of February to July throughout the 2020-2021 school year, the achievement averages of 8.5 were obtained for the first quarter, 8.6 for the second quarter and 8.23 for the third quarter, seeing a notable improvement in accordance with the previous achievement average of the 2019-2020 school year which culminated in 7.9 (Fig. 16).

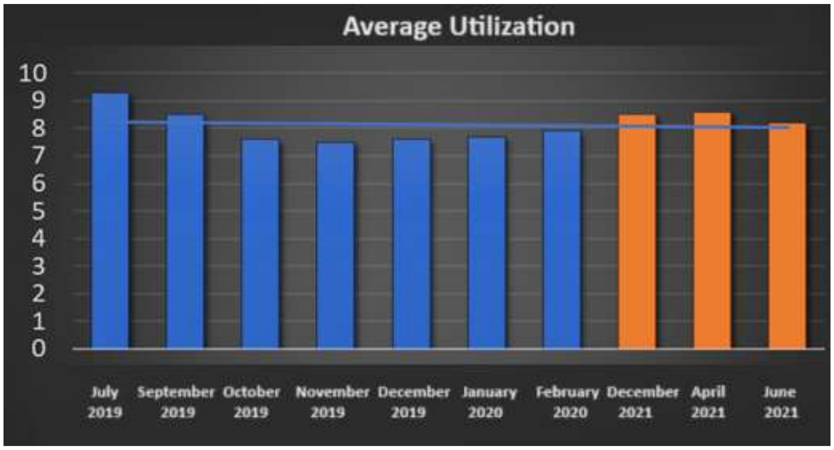


Figure 16. Average utilization 2019 - 2021

5. Conclusions

This article refers to the problem of the low academic performance of students on the subject of technology in the third grade of secondary school located in Reynosa Tamaulipas (Mexico), taking into account the average achievement. For this, an Intelligent Tutor System (ITS) was created, implementing artificial intelligence with the technique of fuzzy logic in such a way that it can assign to the students and subsequently to the group, the optimal learning techniques for learning retention to achieve the expected learning. considering the learning styles of the VARK model and its development index. The ITS provided a correct integration of all modules (student, teacher, and domain), facilitating the acquisition of learning, thus gradually increasing the average achievement of the group, it is based on the results obtained in the 2020 - 2021 school year.

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