A Novel Student Performance Evaluation Model Based on Fuzzy Logic for Distance Learning

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Abstract – Distance learning is an education model in which the educator and the student come together independently of time and place and the learning process is continued. Although it has positive aspects in terms of time and space, it has limitations such as weak interaction and poor functioning of evaluation processes. Assessment systems often include multiple-choice or open-ended questions. In other words, the result is evaluated in solving a given problem, and the student's actions can be ignored until the result is reached. In this study, while evaluating student performance, the student's behavior during the semester and the distractor weight coefficient for multiple-choice exams were added, and a performance evaluation was made on the student's incorrect answers. The proposed model was created based on fuzzy logic, and the uncertainties in the evaluation were attempted to be eliminated.

Citation: Esin Özseven, B., Çağman, B. (2022). A Novel Student Performance Evaluation Model Based on Fuzzy Logic for Distance Learning. International Journal of Multidisciplinary Studies and Innovative Technologies, 6(1): 29-37.

I. INTRODUCTION

Education is defined as the process of creating desired change in people's behavior intentionally and through their own experiences [1]. To ensure that the individual learns for life, first must be taught. Lifelong learning, on the other hand, can be achieved with developments in information and communication technologies and advances in educational technologies.

Distance learning is an education system in which the educator and the student do not share the same physical environment, without time constraints, synchronously or asynchronously with the help of information technologies, and which provides the opportunity for retrospective repetition [2]. Although distance learning has existed for many years, it has come to the fore and is used more due to the pandemic in 2020. According to UNESCO data, 91.3% of students at all educational levels worldwide were directly or indirectly affected by the pandemic. Some problems have also emerged with the widespread use of distance learning systems. The choice of the educational system to be used, performance evaluation, academic ethics, and attendance are the main educational problems. In addition to these, the inadequacy of technological infrastructures has emerged as a technical problem [3].

With the spread of artificial intelligence methods and their application in every field, they have also found application in educational sciences. Especially since fuzzy logic and inference systems achieve successful results in cases of uncertainty, they are used effectively in educational sciences and their use is increasing [4]. Different cognitive and affective structures of students, uncertainties in assessment and evaluation, and the development of educational technologies form the basis of the increase in artificial intelligence-based applications [5].

One of the important problems in distance learning is how to evaluate student success in problem-solving courses [6]. Current assessment systems often include multiple-choice or open-ended questions. That is, in solving a given problem, the result is evaluated, and the student's actions can be ignored until he reaches the result. When the purpose of the exams is to determine the learning level of the student and to evaluate only successful or unsuccessful lessons that include problem-solving, it will create uncertainty in the determination of the learning level. In such exams, the learning level of the student should be interpreted with more than two results. Fuzzy logic is one of the methods that can be used to provide this kind of evaluation and to remove uncertainty.

In this study, a fuzzy logic-based performance and exam evaluation model that interacts with students is presented to handle these uncertainties more effectively and to measure interaction. The presented model includes a fuzzy logic-based approach to determine the student's subject-based and end-of-term performance.

In the next section of the study, the situation in the literature was examined. In the third section, the materials and methods used for the proposed model are explained. In the fourth section, the obtained results are given. In the last section, the results and discussion are given.

II. RELATED WORKS

Distance learning, which started with the shorthand lesson in the Boston newspaper in 1728, was continued in 1833 with the letter composition lessons given to women by the Swedish University, and schools providing education by letter were established [7]. Then, in 1898, language education was given in Sweden [7]. Later, radio stations related to primary education and education by correspondence were established. With the development of technology, there has been a transition to the web-based distance learning model used today [7].

Currently, there are many studies on software used in distance learning [8]–[13]. In these studies, many software such as Big Blue Button, Openmeetings, Adobe Connect, Electa Live, Blackboard Collaborate, GoToTraning, Perculus, VMukti and WizIQ have been compared.

All the methods that an educator uses to get feedback during or after the learning process can be expressed as assessment and evaluation. Although assessment and evaluation are generally seen as the last stages of education, since learning involves a process, they are needed at every stage of the learning process [14]. For this reason, the evaluation carried out throughout the teaching process is for formative purposes and is aimed at determining the learning level of the student at the end-of-term or at the end-of-chapter. Final exams, assignments, or projects are included in the assessment for level determination [14].

In the literature, in studies for assessment and evaluation and student performance evaluation, artificial neural networks, deep learning, random forest, logistic regression, multilayer perceptron, naive bayes, support vector machines, C4.5, decision trees, k-means, JRIP, J48, k-NN, image processing, and fuzzy inference methods were used [4], [6], [15]–[46]. Since fuzzy logic-based work was done within the scope of the study, the studies carried out with this method are detailed below.

In the studies on performance evaluation, the effects of the educator [15], the exam software [17], [47], the student's movements on the system [20], the attendance status [48], the analysis of the question paper [18], the project evaluation [31], and the expression of the marginal scores with fuzzy inference [36] were mentioned.

Two membership functions and subject-based student scores were used in the study in which student performance was evaluated with fuzzy inference [19]. The fuzzy neural network was used in the study, which takes into account factors such as age, gender, education, past performance, working status, and working environment for the prediction of student performance [49]. In another fuzzy inference-based study, student answers were represented by 7 linguistic expressions as unanswered, very bad, bad, moderate, not bad, good, very good. The linguistic expressions of very good, good, not bad, moderate, bad, and very bad were used in the output of the fuzzy inference system [22]. In studies where fuzzy logic-based performance evaluation was conducted, performance evaluation was conducted using homework, quizzes, midterms, finals, watching videos, reading books, personal development, communication skills, and participation information [25], [26], [50]. While evaluating student performance, there are studies in which past learning levels are used together with the current situation [51], [52]. In these studies, back propagation fuzzy inference [51] and a combination of two fuzzy inference systems were used [52], [53]. In the study, which uses 4-valued feedback fuzzy logic to evaluate student achievement, each value represents the months of the educational process. The output of the system has four values: "more effort required", "as expected", "good" and "very good" [6]. In studies using fuzzy logic in order to eliminate the uncertainty in students' passing scores, the student's success or failure was graded using linguistic expressions [6], [36]. In another study, exam score, participation in forums, absenteeism were used as input parameters for fuzzy inference, and student performance was used as output parameter [45]. According to the results of the study, which examined the effects on the student's final exam performance with fuzzy logic, students with high online assessment grades and self-learning processes showed high performance on the final exam [40], [54]. Nor et al. (2021) compared the mathematics course achievement of students in two rural and urban schools with fuzzy logic. The fuzzy decision maker's inputs include midterm and trial exam grades, and the output includes 5 linguistic values (very weak, weak, moderate, good, and very good). A triangular membership function is used as a membership function [55]. Laksana et al. (2021) used fuzzy logic to determine the final grade of university students. The passing grade was evaluated not only according to the exam grade, but also by including form, quiz, and discipline level, with weak, good, and average linguistic expressions [56].

III. MATERIALS AND METHODS

A. Fuzzy Logic

The basis of fuzzy logic is based on the fuzzy sets study published by Zadeh (1965). In a classical set, an element is either an element of the set or it is not. Therefore, it is shown whether the elements of a classical set belong to the set with values of 0 or 1. In the fuzzy set, the generalization of the classical set is made and the belonging of an element to the set is expressed with a real number in the range of membership degrees [0, 1] [57].

Definition 1. (Fuzzy set) *Let X be a universe. Then a fuzzy set A over X is a function defined as follows:*

$$A = \{x/\mu_A(x)|x \in X, \mu_A(x) \in [0,1]\} \tag{1}$$

where, $\mu_A: X \to [0,1]$ is defined as the membership function, and $\mu_A(x)$ is defined as the membership value of the x element in the A fuzzy set.

Since fuzzy sets cannot be represented with exact lines, venn diagram representations cannot be mentioned and are instead represented by graphs of membership functions. The x-axis of the membership function graph shows the members, and the y-axis shows the degree of membership [57]. Membership functions that are commonly used include the triangle, trapezoid, gaussian, and bell curve. Since the triangle membership function is used in the proposed model, the details of the triangle membership function are given below.

The triangle membership function is expressed with three members on the x-axis. For example, the triangle membership function for the values 2, 4, and 6 is given in Equation 2 and its graph is given in Figure 1.

$$\mu_A(x; 2,4,6) = \begin{cases} \dfrac{x-2}{4-2}, & 2 \le x \le 4 \\ \dfrac{6-x}{6-4}, & 4 \le x \le 6 \\ 0, & x > 6 \; or \; x < 2 \end{cases} \tag{2}$$
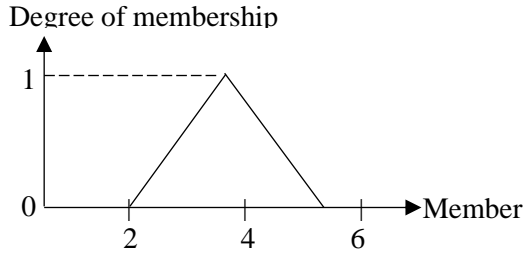

Fig. 1. Example of triangle membership function graph

B. Fuzzy Logic Based Systems

Fuzzy logic was made more flexible by starting from the thought of the inability to express a proposition as true or false, and the proposition was evaluated with fuzzy verbal variables such as some true, some false, very false. Concepts related to fuzzy logic are used in many areas of daily life. For example, in classical logic, 65 exam grades are considered successful and 64 unsuccessful, while in fuzzy logic, this situation can be expressed as 64 less successful. The block diagram of a fuzzy logic-based system is given in Figure 2.
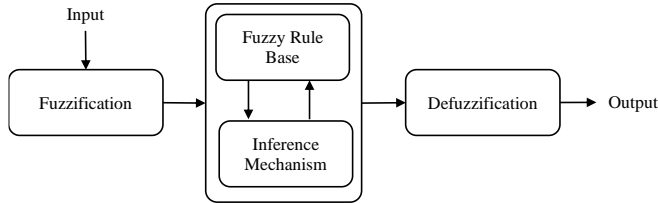

Fig. 2. Block diagram for fuzzy logic based systems [58]

Fuzzification is the conversion of the values used in the input of the system into fuzzy values. The fuzzy rule base contains the table of rules that will be used for the system, expressed as IF-THEN. While writing these rules, all outputs to be obtained depending on the input are used. Thus, each rule logically connects a part of the input space to the output space. All these contexts form the rule base. On the other hand, the inference mechanism ensures that the system behaves with an output by bringing together all the relations established between the input and output fuzzy sets in the fuzzy rule base. The Mamdani and Takagi-Sugeno methods are commonly used for the inference mechanism. In the Mamdani method, "min" is used if the rules are connected with "and" and "max" is used if they are connected with "or" [23]. The output of the inference mechanism will also be the fuzzy set. Defuzzification is the conversion of fuzzy expressions obtained after inference into expressions used in the real world. [58]. There are various methods in the literature that can be used for defuzzification [59].

IV. A PROPOSED MODEL FOR ASSESSING STUDENT ACHIEVEMENT

The proposed model has been divided into 2 categories: activities during the semester and performance evaluation at the end of the term. The activities during the semester include multiple choice exams, classical exams, projects, research, and homework methods. In addition to the activities during the semester, the end-of-term performance includes materials, end-of-chapter evaluations, and attendance at classes during the semester.

The method of Chen and Lee (1999) was used for the classical exam, project, research, and homework, among other activities during the semester [60]. A new model has been proposed by adding the distractor weight, which allows the student to be evaluated on wrong answers in multiple-choice exams.

A. Performance Evaluation During the Semester

Two different approaches based on fuzzy decision-making were used to evaluate activities during the semester, such as the e-exam. The first of these is the evaluation of students' work with classical exams, projects, research, and homework. In this approach, linguistic expressions from Chen and Lee (1999) were used [60]. These expressions are of eleven levels: extremely good (EG), very very good (VVG), very good (VG), good (G), not bad (NB), medium (M), slightly bad (SB), bad (B), very bad (VB), very very bad (VVB), and extremely bad (EB). For these levels, EG=1, VVG=0.99, VG=0.9, G=0.8, NB=0.7, M=0.6, SB=0.5, B=0.4, VB=0.24, VVB=0.09, EB=0 satisfaction levels were specified [60]. The question score and the total exam score are calculated by using these satisfaction levels and the values given by the educator in the range of 0–1 for each level.

The other proposed method for assessing students' exams is for multiple-choice exams. Especially in lessons involving numerical operations, very small mistakes can change the answer to the question. For this reason, a more objective evaluation of such courses can be obtained by examining the student's question-solving stages. However, the applicability of this in distance learning systems is not very possible. Therefore, unlike the literature, in our proposed method, Question Based Response Time (QBRT), Question Difficulty Level (QDL), Distractor Weight (DW), and Question Type (QT) data were used. The method of Chen and Lee (1999) was used to calculate the effect of the output of the fuzzy system on the exam score. QBRT is the time taken to answer each question. QDL is the difficulty level set by the trainer for each question. In lessons with numerical content, very small errors can change the result and cause the result to be incorrect even if all operations are correct. Since the test exams are evaluated only as true or false, the student may fail in this case. To prevent this negativity, the DW expression has been determined. With DW, a weight between 0 and 1 is determined for each option, and this situation is included in the evaluation. For example, if the student can identify the entire map for a concept map-based question, a weight of 1 can be used for the correct answer, and a weight of 0.5 can be used for the relevant option if they know 70% of it. QT, on the other hand, was used to determine the multiple choice (MC) or true/false (TF) question type. In the proposed method, QBRT, QDL, and QT are used as inputs to the fuzzy inference system. DW was taken into consideration while calculating the weights of the question scores.

The linguistic expressions used for QBRT are very fast (VF), fast (F), moderately fast (MF), slow (S), and very slow (VS). The membership functions of the QBRT parameter of the set $x=[0,t]$, with the number of questions n, the duration of

the exam t_{total}, and the average response time $t = \frac{t_{total}}{n}$, are given below.

$$\mu_{VF}(x) = \begin{cases} 1, & 0 \leq x \leq t * 0.25 \\ \dfrac{t * 0.5 - x}{t * 0.25}, & t * 0.25 \leq x \leq t * 0.5 \end{cases} \quad (3)$$

$$\mu_F(x) = \begin{cases} \dfrac{x - t * 0.25}{t * 0.25}, & t * 0.25 \leq x \leq t * 0.5 \\ \dfrac{t - x}{t * 0.5}, & t * 0.5 \leq x \leq t \end{cases} \quad (4)$$

$$\mu_{MF}(x) = \begin{cases} \dfrac{x - t * 0.5}{t * 0.5}, & t * 0.5 \leq x \leq t \\ \dfrac{t * 1.5 - x}{t * 0.5}, & t \leq x \leq t * 1.5 \end{cases} \quad (5)$$

$$\mu_S(x) = \begin{cases} \dfrac{x - t}{t * 0.5}, & t \leq x \leq t * 1.5 \\ \dfrac{t * 2.25 - x}{t * 0.75}, & t * 1.5 \leq x \leq t * 2.25 \end{cases} \quad (6)$$

$$\mu_{VS}(x) = \begin{cases} \dfrac{x - t * 1.5}{t * 0.75}, & t * 1.5 \leq x \leq t * 2.25 \\ 1, & t * 2.25 \leq x \leq t_{toplam} \end{cases} \quad (7)$$

For example, since the average time for each question in a 12-minute exam consisting of 4 questions will be 3 minutes, the membership function graph of the question-based response time of the set *x=[0.180]* is given in Figure 3.
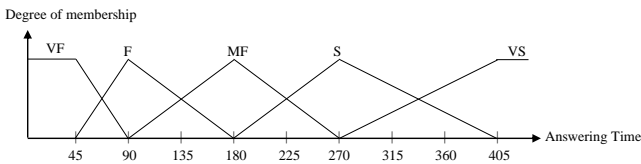

Fig. 3. Example membership function for question-based answering time

Linguistic expressions used for the QDL are very difficult (VD), difficult (D), medium easy (ME), easy (E), and very easy (VE). The membership function graph for the QDL is given in Figure 4.
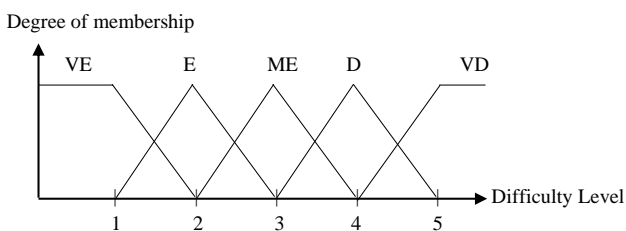

Fig. 4. Membership function used for question difficulty level

The linguistic expressions of Chen and Lee (1999) were used in the output of the created fuzzy model [60]. The membership function graph used for the question result (QR), which expresses the output of the fuzzy model, is given in Figure 5.
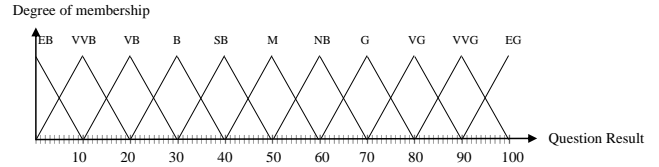

Fig. 5. Membership function used for the question result

B. End of Term Performance Evaluation

To evaluate the end-of-term student performance, e-exam, material usage, end-of-chapter evaluations and attendance to classes were considered. A student can have more than one grade related to the relevant course. The impact rates of these exams will vary according to the relevant institution. For this reason, it is recommended to use a single exam grade obtained after the calculation according to the impact rates of the relevant institution in performance evaluation. In the material usage part, the completion rate of each training material, the difficulty level, and the importance level of the relevant material were used. The success of the student after each chapter is evaluated by the end-of-chapter evaluations. These evaluations are also effective at assessing end-of-term performance. If there is no end-of-term evaluation for the relevant course, this parameter will be ineffective in the performance evaluation. Another evaluation criterion is the student's attendance at classes. This parameter will also be used as a factor in performance evaluation.

The end-of-term performance evaluation is based on fuzzy inference, and the diagram of the relevant module is given in Figure 6.
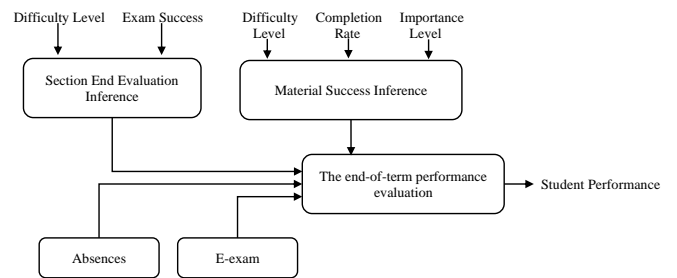

Fig. 6. Fuzzy inference module for performance evaluation

Inference at the end-of-chapter includes the evaluation of the exams at the end of the relevant courses. While making this evaluation, the difficulty level of the department and the success of the exam were used. While calculating the exam success, the fuzzy evaluation system used in the e-exam module was used, and the eleven levels given in Figure 5 were used as output. For the difficulty level, VD, D, ME, E, and VE levels were used. These values are used as the input of the fuzzy inference system and the output of the end-of-chapter evaluation result as eleven levels.

The material success inference includes the use of the educational materials defined for the relevant course by the student. While making this evaluation, the completion rate, difficulty level, and importance level of the material were used as the inputs of the inference system, and the material success

was used as the output. The levels of all completed (AC), three-quarters completed (TQC), half completed (HC), quarter completed (QC), and never done (ND) levels were used for the completion rate. For the difficulty level VD, D, ME, E, and VE levels were used. The very important (VI), important (I), moderate (M), low important (LI), and very low important (VLI) were used for the importance levels. Eleven-level linguistic expressions in Figure 5 were used as output. [60].

The effect of course attendance on performance is subjective and depends on the instructor of the course. Absences of 30% or more are expressed as absentee (AS), absences between 20% and 29% are expressed as less continuous (LC), absences between 10% and 19% are expressed as continuous (C), and absences below 10% are expressed as very continuous (VC).

V. RESULTS FOR THE PROPOSED MODEL

A. Results for Evaluation During the Semester

Two different approaches based on fuzzy inference were used to evaluate student performance during the semester. The first of these is the evaluation method that students will present in written form in the form of classical exams, projects, research, and assignments. In this approach, linguistic expressions from Chen and Lee (1999) are used [60]. An example of the application of this method is given in Example 1.

Example 1. Let's evaluate according to the method of Chen and Lee (1999) for a classical exam consisting of 3 questions or criteria.

Table 1. Dataset for Example 1

Questions or Criteria	Score	Satisfaction Levels (SL)									
		EG	VVG	VG	G	NB	M	SB	B	VB	VVB	EB
1	30	0.0	0.0	0.2	0.5	0.9	0.0	0.0	0.0	0.0	0.0	0.0
2	30	0.0	0.0	0.0	0.0	0.0	0.8	0.5	0.0	0.3	0.0	0.0
3	40	0.0	0.0	0.0	0.0	0.7	0.6	0.0	0.2	0.0	0.0	0.0

The satisfaction levels given in Table 1 were given by the trainer for each question/criterion. Using this information, the satisfaction level for each question is calculated as follows.

$$SL(1) = \frac{0.2 * VG + 0.5 * G + 0.9 * NB}{0.2 + 0.5 + 0.9}$$
$$= \frac{0.2 * 0.9 + 0.5 * 0.8 + 0.9 * 0.7}{0.2 + 0.5 + 0.9} = 0.75625$$

$$SL(2) = \frac{0.8 * M + 0.5 * SB + 0.3 * VB}{0.8 + 0.5 + 0.3}$$
$$= \frac{0.8 * 0.6 + 0.5 * 0.5 + 0.3 * 0.24}{0.8 + 0.5 + 0.3} = 0.50125$$

$$SL(3) = \frac{0.7 * NB + 0.6 * M + 0.2 * B}{0.7 + 0.6 + 0.2}$$
$$= \frac{0.7 * 0.7 + 0.6 * 0.6 + 0.2 * 0.4}{0.7 + 0.6 + 0.2} = 0.62$$

The satisfaction level of each question is multiplied by the score of the relevant question and the total score is calculated by summing them.

$$Exam\ Result = SL(1) * 30 + SL(2) * 30 + SL(3) * 40 = 62.525$$

In the other approach, QBRT, QDL, DW and QT data were used to evaluate exams containing multiple choice questions. A rule base containing 51 rules belonging to the fuzzy model created for the evaluation of multiple-choice questions was created. The output of the rule base includes eleven linguistic statements by Chen and Lee (1999). After the output of the fuzzy inference system was obtained, the question scores were calculated using satisfaction levels and DW. In this proposed method, since the correct answers are included in the fuzzy inference system, depending on the QBRT and QDL of the correct answer, a decrease may be observed in the exam success compared to the classical assessment. For this reason, 2-option evaluation is recommended for exam success. In the first method, all questions are included in the fuzzy inference system. The second method is to insert only the wrong answers into the fuzzy inference system.

Example 2. Information for an exam consisting of 5 MC questions, 20 points per question and 20 minutes in duration, is given below. Let's calculate student success in line with this information.

Table 2. Dataset for Example 2

Question	QDL	Correct Answer	DW for each choice					Student Answer	QBRT
			A	B	C	D	E		
1	1	A	1.0	0.0	0.4	0.0	0.2	E	110 sec
2	3	C	0.0	0.2	1.0	0.0	0.0	C	400 sec
3	2	B	0.0	1.0	0.2	0.5	0.3	B	65 sec
4	5	E	0.0	0.0	0.0	0.0	1.0	E	230 sec
5	1	D	0.2	0.0	0.0	1.0	0.0	A	195 sec

According to the information given, since the average time for each question will be 4 minutes, the membership functions of the set *x=[0,240]* and the QBRT membership function graph are given below.

$$\mu_{VF}(x) = \begin{cases} 1, & 0 < x \le 60 \\ \dfrac{120 - x}{60}, & 60 \le x \le 120 \end{cases}$$

$$\mu_F(x) = \begin{cases} \dfrac{x - 60}{60}, & 60 \le x \le 120 \\ \dfrac{240 - x}{120}, & 120 \le x \le 240 \end{cases}$$

$$\mu_{MF}(x) = \begin{cases} \dfrac{x - 120}{120}, & 120 \le x \le 240 \\ \dfrac{360 - x}{120}, & 240 \le x \le 360 \end{cases}$$

$$\mu_S(x) = \begin{cases} \dfrac{x - 240}{120}, & 240 \le x \le 360 \\ \dfrac{540 - x}{180}, & 360 \le x \le 540 \end{cases}$$

$$\mu_{VS}(x) = \begin{cases} \dfrac{x - 360}{180}, & 360 \le x \le 540 \\ 1, & 540 \le x \le 1200 \end{cases}$$
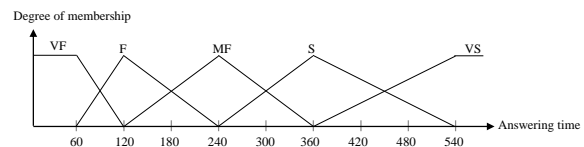

Fig. 7. QBRT membership function

After fuzzification, the values given in the table below were obtained for each question. The rules triggered by each question were determined, and the Mamdani inference method was used.

Table 3. Data obtained after fuzzification for Example 2

	QBRT	QDL	Rule	QR	DW	Question Score
1	0.17 VF and 0.83 F	VE	NB, M	0.17 NB or 0.83 M	0.2	(0.17*0.7+0.83*0.6)* 0.2*20=2.468
2	0.78 S and 0.22 VS	ME	M, SB	0.78 M or 0.22 SB	1.0	(0.78*0.6+0.22*0.5)* 1*20=11.56
3	0.92 VF and 0.08 F	E	G, NB	0.92 G or 0.08 NB	1.0	(0.92*0.8+0.08*0.7)* 1*20=15.84
4	0.083 F and 0.917 MF	VD	VVG, VG	0.083 VVG or 0.917 VG	1.0	(0.083*0.99+0.917*0 .9)*1*20=18.15
5	0.38 F and 0.62 MF	VE	M, SB	0.38 M or 0.62 SB	0.2	(0.38*0.6+0.62*0.5)* 0.2*20=2.152
					Exam Score	50.17

When the classical evaluation is made with these values given as an example, the exam score is 60. When the evaluation was made according to the question type, response time, distractor weight, and difficulty level, and when all the questions were put into the fuzzy inference system, the result was calculated as 50.17. If only wrong answers are inserted into the fuzzy inference system, the result will be 64.62.

B. Results for End of Term Evaluation

The end-of-chapter evaluation inference includes the evaluation of the exams at the end of the relevant courses. While making this evaluation, the difficulty level of the chapter and the success of the exam were used. While calculating the success of the exam, the fuzzy evaluation system used in the e-exam module was used, and eleven levels were used as output: EG, VVG, VG, G, NB, M, SB, B, VB, VVB and EB. For the difficulty level, VD, D, ME, E, and VE levels were used. These values are used as the input of the fuzzy inference system and the output of the end-of-chapter evaluation result as eleven levels. This model was applied to each chapter, and output was obtained for as many as the number of chapters. The average of these outputs is used as an input for performance evaluation. A rule base consisting of 55 rules was created for the end-of-chapter evaluation.

The material achievement inference includes the use of the educational materials defined for the relevant course by the student. While making this evaluation, the completion rate, difficulty level, and importance level of the material were used as the inputs of the inference system, and the material success was used as the output. AC, TQC, HC, QC, and ND levels were used for the completion rate. For the difficulty level, VD, D, ME, E, and VE levels were used. For the importance level, the levels of VI, I, M, LI, and VLI were used. Eleven levels were used as outputs: EG, VVG, VG, G, NB, M, SB, B, VB, VVB, and EB rule base consisting of 120 rules for material success inference was created.

The effect of course attendance on performance is subjective and depends on the instructor of the course. Absences of 30% and above are expressed as AS, between 20% and 29% as LC, between 10% and 19% as C, and below 10% as VC.

After defining the inputs for performance evaluation, the output is determined according to the rule base consisting of 4236 rules. In the light of this information regarding performance evaluation, a sample evaluation is given below.

Example 3. The student statuses for a course with two chapters are given below. Let's evaluate student achievements with the performance evaluation system recommended for these situations.

Table 4. Data set for Example 3

	Chapter 1				
	The end-of-chapter		Material Success		
	Exam Score	Difficulty Level	Completion Rate	Difficulty Level	Importance Level
Student 1	86	D	75%	ME	I
Student 2	62	D	50%	ME	I
Student 3	52	D	25%	ME	I

	Chapter 2					E-exam		Absences
	The end-of-chapter		Material Success					
	Exam Score	Difficulty Level	Completion Rate	Difficulty Level	Importance Level	Exam 1	Exam 2	
Student 1	77	VD	25%	D	VI	74	62	10%
Student 2	84	VD	100%	D	VI	92	97	5%
Student 3	58	VD	50%	D	VI	83	84	25%

The fuzzification of the student data given in Table 4 is given in Table 5. The defuzzification result is given in Table 6. The midpoint method of greatest membership was used when performing the defuzzification and for the end-of-chapter and material success of the 2 units.

Table 5. Fuzzification for Example 2

	Chapter 1						
	The end-of-chapter			Material Success			
	Exam Result	**Difficulty Level**	**Rule**	**Completion Rate**	**Difficulty Level**	**Importance Level**	**Rule**
Student 1	0.4 VG and 0.6 VVG	D	0.4 VG or 0.6 VVG	TQC	ME	I	VG
Student 2	0.8 FD and 0.2 G	D	0.8 NB or 0.2 G	HC	ME	I	G
Student 3	0.8 M and 0.2 NB	D	0.8 NB or 0.2 NB	QC	ME	I	NB
	Chapter 2						
	The end-of-chapter			Material Success			
	Exam Result	**Difficulty Level**	**Rule**	**Completion Rate**	**Difficulty Level**	**Importance Level**	**Rule**
Student 1	0.3 G and 0.7 VG	VD	0.3 VG or 0.7 VG	QC	D	VI	G
Student 2	0.6 VG and 0.4 VVG	VD	0.6 VG or 0.4 EG	AC	D	VI	EG
Student 3	0.2 M and 0.8 NB	VD	0.2 NB or 0.8 G	HC	D	VI	VG

E-exam			Absences
Exam 1	**Exam 2**	**Result**	
max(0.6 G, 0.4 VG)=G	max(0.8 NB, 0.2 VG)=NB	G	C
max(0.8 VVG, 0.2 EG)=VVG	max(0.3 VVG, 0.7 EG)=EG	EG	VC
max(0.7 VG, 0.3 VVG)=VG	max(0.6 VG, 0.4 VVG)=VG	VG	LC

Based on the information given in the table above and the rule tables, the performance evaluation results are given in the table below.

Table 6. Defuzzification for Example 2

	Chapter 1			Chapter 2			The end-of-chapters	Materials Success
	The end-of-chapter		Mat. Baş	The end-of-chapter		Mat. Baş		
	Fuzzification expression	**Result**	**Rule**	**Fuzzification expression**	**Result**	**Rule**		
Student 1	VVG	90	VG	VG	80	G	85 (0.5 VG and 0.5 VVG)	VG
Student 2	NB	60	G	VG	80	EG	70 (İ)	VVG
Student 3	NB	60	NB	G	70	VG	65 (0.5 NB and 0.5 G)	G

	The end-of-chapters	Materials Success	E-exam	Absences	Triggered Rule	**RESULT**
Student 1	85 (0.5 VG and 0.5 VVG)	VG	G	C	NB	60
Student 2	70 (G)	VVG	EG	VC	VVG	90
Student 3	65 (0.5 NB and 0.5 G)	G	VG	LC	0.5 SB or 0.5 M	50

VI. CONCLUSION AND DISCUSSION

As a result of the reflection of the developments in information technologies on education, distance learning studies focus on many subjects, especially increasing teacher-student interaction, focusing on student-centered education, building academic confidence, and objective evaluation.

An important issue for distance learning systems is the objective and student-centered evaluation of student performance. In the studies, not only exam scores but also student movements within the system, material use, and class participation factors were taken into account in order to evaluate student performance [6].

Student success is planned to be realized through end-of-chapter evaluation, course attendance, and e-exams. For multiple-choice questions, the distractor weight was added to the answer choices and the evaluation was made accordingly. Thus, scoring was not done on exact true and false, but also on incorrect answers according to the distractor weight. In addition, the time the student spent on the questions was also included in the assessment. As a result, a model that offers a very valuable evaluation opportunity for distance learning has been proposed. The proposed model can be used for all distance education courses, especially applied courses. In addition, since the e-exam evaluation module can work on a question-based basis, it can also be used for project and application-based evaluations.

Authors' Contributions

The authors' contributions to the paper are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

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