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Research paper

Fuzzification of Items of Media and Educational Materials and Tools

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Abstract

Background and Objectives: The purpose of this study is to propose a solution for using large fuzzy sets in assessment tasks with a significant number of items, focusing on the assessment of media and educational tools. Ensuring fairness is crucial in evaluation tasks, especially when different evaluators assign different ratings to the same process or their ratings may even vary in different situations. Also, previous non-fuzzy assessment methods show that the mean value of assessors scores is not a good representation when the variance of scores is significant. Fuzzy evaluation methods can solve this problem by addressing the uncertainty in evaluation tasks. Although some studies have been conducted on fuzzy assessment, but their main focus is fuzzy calculations and no solution has been proposed for the problem arising when fuzzy rule set is considerably huge.
Methods: Fuzzy rules are the main key for fuzzy inference. This part of a fuzzy system often is generated by experts. In this study,15 experts were asked to create the set of fuzzy rules. Fuzzy rules relate inputs to outputs by descriptive linguistic expressions. Making these expressions is so more convenient than if we determine an exact relationship between inputs and outputs. The number of fussy rules has an exponential relationship with the number of inputs. Therefore, for a task with more than say 6 inputs, we should deal with a huge set of fuzzy rules. This paper presents a solution that enables the use of large fuzzy sets in fuzzy systems using a multi-stage hierarchical approach.
Results: Justice is always the most important issue in an assessment process. Due to its nature, a fuzzy calculation-based assessment provides an assessment in a just manner. Since many assessment tasks are often involved more than 10 items to be assessed, generating a fuzzy rule set is impossible. Results show the final score is very sensitive to slight differences in score of an item given by assessors. Besides that, assessors often are not able to consider all items simultaneously to assign a coefficient for the effect of each item on final score. This will be seriously a problem when the final score depends on many input items. In this study, we proposed a fuzzy analysis method to ensure equitable evaluation of educational media and instructional tools within the teaching process. Results of none-fuzzy scoring system show that final score has intense variations when assessment is down in different times and by different assessors. It is because of the manner that importance coefficients are calculated for each item of assessment. In fuzzy assessment no importance coefficient is used for each item.
Conclusion: In this study, a novel method was proposed to determine the score of an activity, a task, or a tool that is designed for learning purposes based on Fuzzy sets and their respective calculations. Because of the nature of fuzzy systems, approximate descriptive expressions are used to relate input items to final score instead of an exact function that is impossible to be estimated. Fuzzy method is a robust system that ensure us a fair assessment.

Introduction

Fair assessment is an important aspect in educational programs and fuzzy assessment is an approach to the fair assessment.

Simple statistical methods (such as averaging) are not so fair for an assessment task. It is because of three the following reasons:

- ✓ Often it is not so easy to assign an exact score or point to an item. In other words, when an expert is asked to set a point to an item at different times, there is a high probability that he/she will assign different points to the same item.
- ✓ An item of an activity may not be compared with other items when assigning a point to it. When assigning a point to an item, experts will focus exclusively on that specific item. Therefore, they may review the questionnaire and change the score of an item many times.
- ✓ Several experts will cause a diverse value for the point of a particular item.

In this study, we are going to deal with the concept and benefits of fuzzification of assessment items, with a focus on Media and Instructional Tools Assessment. Justice is an important component in an assessment task when different assessors may give different points to the same process. Even an assessor generally gives different points in different situations. The fuzzy assessment method will overcome this failure in assessment. Fuzzy calculations are an AI tool to deal with vague or approximate situations. It is always easier to assign an approximate value instead of the exact value to a variable.

Grade given by the teacher to a student can be optimized by using fuzzy logic [1].

Development of modern education, along with traditional learning, also requires using new assessment models (Glushkova et al, 2024) [2]. By utilizing assessments, researchers can acquire valuable data to recognize patterns, variances, and relationships within the dataset, ultimately enhancing knowledge and research development [3]. Penfield et al. (2016) [4], [5] and Andrade (2019) [6] highlighted the importance of assessment in fostering informed decision-making and augmenting research outcomes.

This method advances the interpretation and analysis within academic research by guaranteeing a more accurate depiction of subjective data and offering a flexible framework to accept varying degrees of imprecision or ambiguity.

Fuzzification, as a method, is crucial for capturing the complexity of real-world events that are inherently difficult to measure or categorize accurately (Markov et al. (2022)) [7].

The fuzzy calculations utilized here is based on Mamdani fuzzy inference [8]. Also Yunan and et al. [2020] [9] used this method of inference in their study. This is implemented by three main blocks: 1- fuzzification using membership functions, 2- aggregation fuzzy rules and 3- defuzzification using calculating the center of gravity of aggregated rules.

This work focuses on a huge fuzzy rule set that is a gap in similar previous works.

Assessing media and educational materials is so complicated and needs to be precisely down. This article discusses using fuzzification techniques to make the assessment better. Fuzzification helps us understand things that are not easy to put into categories. It works by giving different levels to words to help us grasp complexity. This method helps show data accurately and handles uncertainty well.

The integration of fuzzification techniques significantly enhances the efficacy of questionnaires in media and educational research. By adopting these methods, researchers can surpass the confines of conventional binary response formats, resulting in the collection of more refined and precise data. In media analysis, fuzzification empowers researchers to capture diverse subjective viewpoints and preferences through the inclusion of response choices with varying degrees of agreement. This approach recognizes the variability in individuals' levels of alignment or discord with a statement, leading to a more holistic comprehension of their perspectives. Likewise, within educational research, fuzzification strategies provide a deeper understanding of students' learning journeys. By offering a range of response levels that mirror varying degrees of understanding or skill, questionnaires become more accommodating to different learning preferences and competencies. The utilization of fuzzification techniques ensures that questionnaires transcend rigid binary responses, embracing the intricate nature of human experiences (Reigeluth, Honebein. 2023) [10], [11].

In a multi-item task assessment, a simple technique that quickly comes to mind is an averaging method in which we consider different coefficients for each item. In detail, we can design a questionnaire and ask some experts to determine a coefficient (say between 0 and 1) to assign to each item. In the end, we can consider the average of the given coefficients as the final coefficient for each item. Despite its simplicity, there are many serious problems with this manner due to an important concept we refer to it as "vagueness".

If some people are asked to estimate the weather temperature in degrees centigrade, they never state that the temperature is -7°C, if really it is. But all of them likely say that it is "too cold". In a fuzzy assessment, assessors are asked to use approximate sentences and then the fuzzy system converts it to an exact value. One important issue that our study focuses on and was not the main subject in other similar studies is the number of Fuzzy rules. Fuzzy rules set is an essential part of Fuzzy calculations so if a Fuzzy system has incomplete rules set, results will not be reliable. Rules tell us how different items affect the final result of an assessment in an approximate verbal description. These approximate verbal descriptions are similar to these sentences: "For a gymnast, if her/his errors are low and the time activities are finished is high, then her/his score is high", "If a student solves new math problems in a very short time, then she/he possesses a very high talent in math". A fuzzy calculation system works with these sentences. Fuzzy rules are these if-then formatted sentences.

The rules set are directly related to the items to be assessed. For example, in an assessment problem with 10 effective items in the final score, we will have a set with at least 310 different rules. Making a fuzzy system with a large rule set needs an algorithmic method to be involved.

This article explores how you can handle huge fuzzy sets in a fuzzy assessment problem.

There are some studies on fuzzy assessment tasks in which researchers pay particular attentions to different fuzzy calculations and systems. Many types of fuzzy calculations have been proposed for implementing a fuzzy assessment system. Mostly we have to perform an assessment task using more than 8 items affecting on it. This will lead to a large fuzzy set to be worked on.

A similar study has been published by the author for the assessment of Laboratory Courses in Electronics Engineering, in which the final score of a student is estimated using fuzzy calculations with three sub-activities as input parameters. These items have different contributions to the final score (Musavian, 2013) [12]. Therefore, a fuzzy rule set containing $2^3 = 8$ rules is used to calculate final scores.

Glushkova and her colleagues, (2024) [2] in their research presented a method for university teachers to evaluate their teaching performance using type-II fuzzy sets (T2 FSs). The evaluation indicator system is constructed from teaching attitude, teaching contents, teaching professionalism, teaching methods, and teaching effects. Therefore, this produces a fuzzy set including only $2^5 = 32$ fuzzy rules. Extracting a fuzzy set containing 32 rules cannot be considered a critical issue.

Also (Sheveleva et al, 2023) [13] used only 3 input variables, therefore, a total number of 8 rules were generated. This method of fuzzy calculations was sufficient only for student competency assessment and may not be developed to our task.

In Ryabko et al. (2022) [14], some graduated students were selected as samples to investigate different items affecting the quality of the education system. Therefore, rules are generated automatically. However, a weakness of this method is that these students were taught in that education system, therefore it is not a reliable criterion for assessment.

In Nurhidayah et al. (2022) [15] employees were assessed using only two variables: x_1 : the value of employee work goals. x_2: behavioural values. Therefore, making a set with 22=4 rules is a simple task. Considering only two items for assessment is not what will happen in practical cases.

Raheema (2022) [16] and Rojas (2021) [17] presented A fuzzy system for predicting student achievement throughout their education period.

Course evaluation is a critical part of undergraduate curriculum in computer science (Yan Liu 2022) [18]. In Yan Liu (2022) and et al. study only 4 fuzzy sets have been used for fuzzy inference. They used a Mamdani inference method to implement fuzzy calculations.

In Rahmanian (2021) [19], 12 items were considered for the task of assessment. One type of fuzzy calculation was performed without considering a rule set. In this manner, the fuzzy reasoning block has been omitted from the system, and the benefits of other blocks (such as the defuzzification block which is the last block of fuzzy systems to transform descriptive to quantitative values) are taken under consideration.

Also, in Sun et al. (2021) [20], similar work was performed for university teachers, a few sample rules were used (not all possible rules) merely for developing the calculations. They also used a traditional fuzzification and defuzzification blocks described in (Musavian, 2013) [21].

Antonio Cervero and et al. (2020) [22] analyzed student satisfaction with the use of virtual campuses in university teaching in order to discover the main variables influencing the overall online teaching-learning process that give quality to the virtual educational process, using a fuzzy inference system.

Higher education institutions are currently facing a competitive environment such as the increase in employers‟ demand and the challenges from Industry. Therefore, higher education institutions must ensure that students overcome the challenges in this competitive environment. In order to achieve this, student performance needs to be analyzed systematically by identifying the students‟ deficiencies and advantages. Petra (2021) [23] focused on the student performance analysis per year by using fuzzy logic evaluation methods.

In Alaa et al. (2019), [24] a total of 19 items were used to assess four English skills. Therefore, a rule set containing 219 rules was generated. Such a huge rule set is impossible to be implemented by a questionnaire.

In Namlı and Şenkal (2018) [25] only two input variables were used to estimate the final score. A maximum of $2^5 = 32\, possible$ rules can be generated with 5 input sets. These number of input variables is not so sufficient for a fair assessment and different competencies may be assessed as the same level. Here a defuzzification block can be omitted due to very small number of input variables.

In Yudono (2021) [26] was used only 3 items to do university student admission selection task, so only 8 fuzzy rules could be generated. These items were: Basic Competency, TOEFL Prediction and Interview. The last item is not so observable to assign an exact point to it. Therefore, a fuzzy method is the most suitable way to rate this item.

In Thakre and Chaudhari (2017) [27], Six effective factors for the assessment of teachers were considered with five input fuzzy sets. Therefore, a number of $5^6 = 15625$ fuzzy rules was possible to be gathered. Certainly, this number of rules is too high to be dealt with. Of course, the focus of this study was on fuzzy calculations and it was performed only using 50 (out of 15625 rules). Here some calculations similar to one that in (Musavian, 2013) are used for fuzzification and defuzzification blocks. Obviously considering only 50 rules instead of 15625 will not lead to accurate results.

In Voskoglou (2013) [28] only 3 items were presented for the assessment of students, S1: knowledge of a subject matter. S2: problem-solving related to S1. S3: the ability to adapt properly the already existing knowledge for use in analogous similar cases. Therefore, the rules set comprises up to 23=8 rules. Many student assessment procedures use more than three items to assess students in a fair manner.

In Montero et al. (2005) [29], a final score was estimated based on 5 different activities of students. Due to this number of input sets, $5^5 = 3125$ possible rules would be generated but only 6 rules were used to develop calculations. Considering only 6 items instead of 3125 rules means that the purpose of this study is developing fuzzy calculations.

In this paper we will discuss and present a hierarchal method to utilize all possible rules (in a big rule set) in a fuzzy rule base system. Most similar works with more than 5 items of assessment focused on calculations instead of dealing with a big rule set. They ignored many rules and developed their fuzzy based calculations using a very limited number of possible rules.

Traditional fuzzy calculations may vary in terms of fuzzy membership functions. many studies are focused on the effect of membership functions on final results. We showed that the type of membership function is not so critical for the task of assessment, since these membership functions are identical for all assesses.

Technical Work Preparation

Zadeh's study [30] (1965, as cited in Adeyanju et al. 2021 [31]) proposed Fuzzy sets, the core of Fuzzy logic systems in 1965. Fuzzy logic solves problems that are not handled by well-known logic systems that is crisp (either 0 or 1) logic. Judging is always unfair because of lacking in our knowledge about the universe. So, one cannot describe a complicated system in detail. For example, we aren't able to express the temperature exactly in degrees Celsius if we do have not a temperature sensor. But rather we can describe the temperature by some linguistic words, such as "the weather is very cold", "is rather cold", "is not so cold" and these kinds of expressions. Using these vague expressions, you can help someone to choose a suitable cloth on a winter day. Fuzzy sets are the key factor in understanding fuzzy systems.

- **Fuzzy Sets**

Sometimes it is not so simple to classify objects based on some of their scalar features. Suppose that students of a school are to be classified into three classes: Excellent, Good, and Poor students using the following function:

$$Student\ a\ belongs\ to \begin{cases} Excellent & if\ M > 17 \\ Good & if\ 14 < M < 17 \\ Poor & if\ M < 14 \end{cases}$$

in which M is the mean score of each student. Since each student only belongs to one set, these are referred to as crisp sets. Consider two students with mean scores equal to 13.9 and 14.1. The former is classified as Poor students and the second as Good students. However, these two students are not very differently talented. But they will be laid in completely different sets using a crisp classification method.

If we apply the crisp classification method to the task of choosing a suitable cloth in cold weather, probably we have to wear another cloth when the temperature is -1oC compared to when the temperature is +1oC.

Fuzzy methods fix the mentioned problem in decision-making tasks. In a fuzzy system, it is supposed that an object belongs to all sets. That is a student belongs to the three above sets, regardless of his/her scores. The main question is: "How we can design a system so that although we consider an element belongs to all sets, the system still can properly work?". The solution is so simple, an element is a member of all sets, with a different membership degree. Membership degree is an important parameter in fuzzy sets and has a value in the range of [0…1]. For example, a student with a mean score equal to 10 is a member of the set Excellent, but with a membership degree too close to 0, but another student with a score of 20 belongs to that set with a membership of 1. Membership degrees are determined using some mathematical functions called membership functions. Fig. 1 shows some typical membership functions for a fuzzy system with three sets.

In Fig. 1 we can see that a student whose mean score is 16, belongs to the sets Excellent, Good, and Poor with the value of membership degrees equal to 0.3, 0.3, and 0 respectively.

The membership functions of Fig. 1 are linear, but non-linear functions are also used in engineering problems such as pattern recognition. Linear functions are sufficient in problems such as the task in this study. One important aspect is the overlap of functions. The amount that functions overlap with each other, can be suggested by experts in the field.

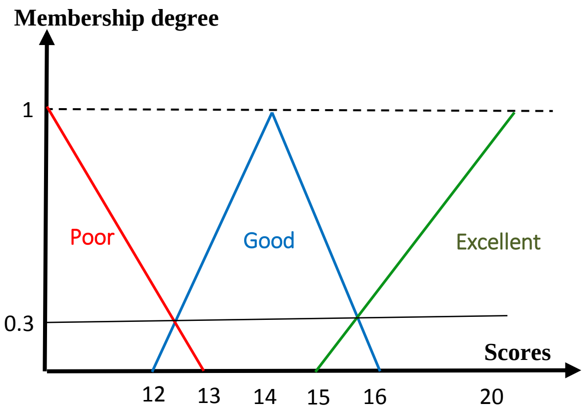

Fig. 1: a typical membership function for the student's classification problem.

There are some other mathematical membership functions such as sigmoidal functions. Results in (Musavian, 2013 [12]) shows that triangular functions shown in figures 1 and 2, not only are simpler in implementation but generate more reasonable results.

- **Fuzzy Rules**

In the two previous circumstances, only one category of sets was used. In practical problems, two categories of sets are demanded, that is input and output fuzzy sets. We need these two categories of sets to produce fuzzy rules.

We can write the task of problem-solving in mathematical language as $y = f(x_1, x_2, \dots)$ in which the input x_i becomes the output y by the system f. f cannot be made so easy by classical calculations such as statistical methods. f can be considered as a mathematical relationship, but what kind of math functions (such as sinusoidal, exponential, polynomial, etc. can be supposed to model our system? Therefore, describing an exact relation between input and output is rather impossible. Assume you are driving on a road at a speed of 70 km/hrs.

If an obstacle is seen at a distance of 20m, you should apply a force equal to F on the brake pedal for time T. You need to know the physical formula necessary for calculating F and T. Besides you have to know also the amount of friction coefficient between tires and the pavement.

Do you drive in such a manner? Of course not! You just know some rules from your experiences from driving: "If the speed is high AND the obstacle is so near, then push down on the pedal harder". Or like this: "If the speed is low AND the obstacle is far, then push down on the pedal gently ".

These are some uncertain but applicable rules, so a driver can control the car using these rules.

A fuzzy rule is a conditional statement that describes a decision-making guide but in a very approximate manner. It has an IF-THEN structure:

if x is A ***then*** y is B.

in which the antecedent part is "x is A" and the statement "y is B" is known as the consequent. Often Fuzzy rules have multi-part antecedents. A Fuzzy rule with a multi-part antecedent has a form as follows:

if x1 is A1 AND/OR x2 is A2 AND/OR ... AND/OR xn is An ***then*** y is Bj.

For example, in the choosing warm clothes problem we have:

if(*rather cold* AND *high wind*) OR *too cold* ***then*** *thick clothes*.

In the above rule we can recognize that when it is too cold, regardless of the speed of wind, we choose a thick cloth. Therefore, this rule can be broken into two rules as follows:

if (*rather cold* AND *high wind*) ***then*** *thick clothes*.

if *too cold* ***then*** *thick clothes*.

For computational reasons, we prefer to use multiple rules rather than one rule with multi-part antecedents.

x and y are known as input and output variables. In our task, x represents factors affecting scoring and y represents the final score. In the problem of choosing warm clothes, weather temperature and speed of wind are two factors that affect choosing suitable clothes. Therefore, some rules are expected to have multi-part antecedents. As it will be mentioned in the next section, size of a fuzzy rule set depends on input variables. The thing that will cause a rule set to be too large to be handled by fuzzy calculation, is the number of items should be assessed in a justly assessment task. Fuzzy rules are developed by experts in a fuzzy system. In an assessment task, experts are who know how much an item contributes in final score. As mentioned in section 2.6, experts were involved to generate fuzzy set in two steps.

- **Input and Output Fuzzy Sets**

Consider again two previous problems mentioned before. Each one of these two problems will describe the concept of input and output sets separately so that one describes the input and the other describes the output sets.

In the problem in which students are to be classified into three classes, the three sets of Excellent, Good, and Poor students are output fuzzy sets, as the intention is to put a student in one of the three mentioned sets. For the second problem we can define the following input sets:

Too cold, rather cold, temperate (as the first variable).

High, fairly high, gentle, not windy.

Although two example problems only have one category of sets, in practical situations, as at the present work, we have to define both categories of sets.

- **Number of Rules-Based upon Input Variables**

The number of rules in a Fuzzy system depends on the number of input variables. Effective factors in scoring are indeed input variables. As a general formula, we can write:

$$N_r = N_v^{N_s}$$

In which:

N_r: Number of Fuzzy rules

N_v: Number of input variables

N_s: Number of input Fuzzy sets

For example, in an assessment problem with 10 factors determinative of the final score, if we define 3 input sets (High, Medium, Low), then we will describe 310 different rules. This number of rules is too much to be generated by experts.

As depicted in table 2, there are 11 items to be considered for our assessment task. This will introduce more than 2000 rules and impossible to be generated by experts. There is no algorithm to sample a finite number of rules among such a huge rule set, therefore, an algorithmic method is needed to be implemented for considering the effect of all rules. In this study, a novel layering method is proposed to consider the effect of all rules.

- **Generating Fuzzy Rules in our Task**

Input and output fuzzy sets should be determined to generate fuzzy rules. As experts in the field confirmed, for an efficient assessment system, it will be sufficient for the number of input sets to be equal to three that is High, Medium, and Low. Fig. 2(a) shows membership functions for input and Fig. 2(b) for output fuzzy sets. On the other hand, more input sets, are closer to a crisp system rather than a fuzzy one. If even we consider the number of input sets to be 5, it will be a very difficult task for experts to define rules.

We consider 5 output fuzzy sets: Excellent, Very good, Good, Medium, and Poor. This number of output sets is not too large to cause confusion to experts who are asked for rule generating. Also, it is not too small to cause an injustice to be down in assessment.

Since the output of a fuzzy system is limited to a small number of sets, it will be very likely that some conditions of input sets, lead to the same result of assessment. In assessment tasks always, there are some conditions where one or more factors dominate other factors. When generating Fuzzy rules, if these dominant factors are evaluated as Excellent, then it will be very likely that we have no choice but to assign the output to the set Excellent.

Suppose the variable x_1 is a dominant variable among the other two, that is x_2 and x_3. If so, the rule:

if x_1 is *Low* ***then*** y is *Poor*.

Represents 9 different rules. In other words, this single rule reduces 27 rules to 19 rules. We proposed a grouping method to convert a large group of rules to a small one so that it can be an appropriate representative for the larger group.

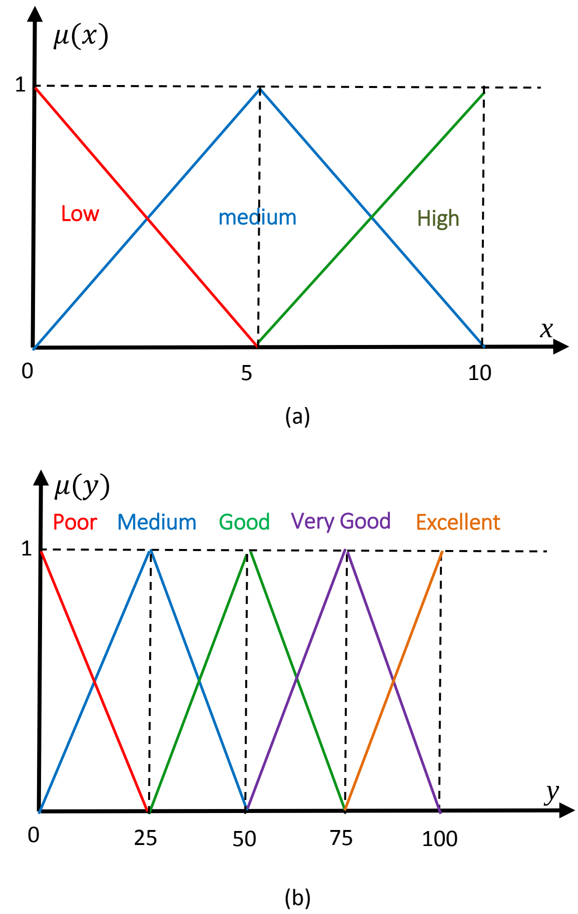

Fig. 2: (a): membership functions of input fuzzy sets used in our task of assessment, (b): membership functions of output fuzzy sets used in our task of assessment.

- **Grouping items**

Grouping items is the first step to reducing input variables. Homogeneous items are brought into one group.

Homogeneity may be defined as having the same effect on the final score.

In other words, all items with a high effect may be categorized in the same group. Fig. 3 shows an example of grouping 10 different items into three groups. All items in a specific group have the same effect on the final score. Now we change a problem including 10 items to a problem with 3 new items.

In the following, we suppose three groups are represented by sub1, sub2, and sub3.

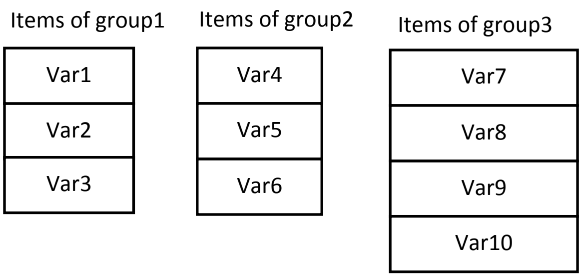

Fig. 3: 10 items are categorized into 3 groups.

The first step is to generate some rules assuming each group is considered as an item. At this step (first level of rule generation procedure), experts are asked to establish rules that relate input sets to output sets with sub1, sub2, and sub3 as input items. So now we have $3^3 = 27$ instead of $3^{10} = 59049$ rules. Now suppose experts confirm that if groups 1 and 3 are evaluated as Low, then a final fuzzy score is evaluated as Poor regardless of what group 3 may be evaluated.

We refer to these two groups as definitive items/groups. Therefore, the following single rule is representative of 27 rules:

if sub1 is *Low* AND sub3 is Low ***then*** output is *Poor*.

Also suppose groups 1 and 3 are again definitive groups if they consist of items with high effects on the final score, so we can similarly write the following rule:

if sub1 is *High* AND sub3 is *High* ***then*** output is *Excellent*.

Table 1: Items for evaluation of instructional media and tools (Assessment forms of the teaching festival at Farhangian University, 2022)

Items	
Introducing the instructional media using a certificate of authenticity (COA)	1
Ease of use, simplicity, and accessibility of instructional media and tools	2
Using creativity in the development of instructional media and tools as well as paying attention to their attractiveness	3
Appropriateness of instructional media and tools with characteristics of learners	4
Consistency, coherence, and coordination across all elements of instructional media and tools	5
Alignment of instructional media and tools with learning objectives, content, and teaching methods	6
Improving the quality of learning in different domains	7
Taking into consideration the different uses of instructional media and tools	8
Interactive instructional media and tools	9
The extent of using IT and ICT in teaching as well as introducing websites that are useful and related to the subject matter	10
Cost-effectiveness of instructional media and tools	11

It should be noted that the two above rules do not imply that the final score depends on only groups 1 and 3, even when sub1 and sub2 are both High (or both are Low).

All rules will be taken into account when mapping input sets onto output sets in a Fuzzy system.

This is why Fuzzy logic is an efficient tool for dealing with uncertain descriptions in the format of if-then statements.

An example of a rule with a three-part antecedent is as follows:

if sub1 is *Med* AND sub3 is High AND sub2 is *High* ***then*** output is *Very good*.

For the reasons mentioned above, input and output sets are assumed to be:

Output sets: Excellent, Very good, Good, Fair, Poor

Input sets: High, Med, Low

In this research, we employed the described analyses to assess an educational tool. These sets will serve as the basis for developing an assessment fuzzy system to assess instructional tools.

- **Assessment of Instructional Media**

Table 1 shows the necessary items for evaluating instructional media and tools approved by Farhangian University of Iran (teachers training center). These items are the same as input variables.

In this study, we proposed a fuzzy analysis method to ensure equitable evaluation of educational media and instructional tools within the teaching process.

Supposing three input sets (Low, Medium, and High) and according to the mathematical permutation formula, there are $3^{11} \approx 177000$ possible rules.

This extra-large group of rules makes it impossible to generate an applicable bank of fuzzy rules. Furthermore, there is no method to choose some rules among these very many rules to be an efficient representative of all possible rules.

Fifteen experts were inquired about how to categorize these eleven items into three groups (see Fig. 4).

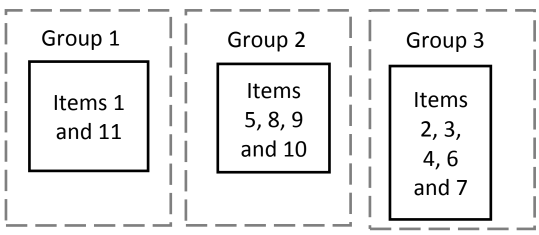

Fig. 4: Grouping of 11 items for assessing instructional media and tools.

- **Between Groups Rules**

Between groups, rules are limited to $3^3 = 27$rules (3 variables and 3 input sets). From Figure (4) we conclude that groups 2 and 3 are definitive, so we can consider the following rules:

R1: ***if*** sub2 is *Low* AND sub3 is *Low* ***then*** output is *Poor*.

R2: ***if*** sub2 is *High* AND sub3 is *High* ***then*** output is *Excellent*.

Between-group rules are summarized in the table shown in Table 2.

- **Within Groups Rules**

Now we focus on each group and assign a descriptive value to each item inside a group. Here each item is compared with other items inside the same group. Since the number of items within each group is much less than all items, it will be much more convenient to construct rules for a sub-system having 3 or 4 items instead of 10 (compare $3^4 = 81$ with $3^{10} = 59049$).

The next step is to determine descriptive values for items within each group. Table 3 shows these values which again are obtained from experts by a questionnaire.

Tables 4(a) to 4(c) show within-group rules for groups G1, G2 and G3.

Table 2: Between groups rules

Rule Number	G_1	G_2	G_3	Fuzzy Output
R_2	×	H	H	*Excellent*
R_3	×	M	H	*Very good*
R_4	×	L	H	*Good*
R_5	H	H	M	*Very good*
R_6	L/M	H	M	*Good*
R_7	L/M	M	M	*Fair*
R_8	H	M	M	*Good*
R_9	H	H	L	*Good*
R_{10}	×	M	L	*Fair*
R_1	×	L	L	*Poor*

× stands for don't care states

Table 3: descriptive values of within-group items

G_1		G_2		G_3	
item	***Fuzzy value***	***item***	***Fuzzy value***	***item***	***Fuzzy value***
1	L	5	M	2	L
11	H	8	M	3	M
		9	H	4	H
		10	M	6	H
				7	M

- **Fuzzy inference**

Fuzzy inference is the process of relating inputs to outputs in a fuzzy manner. This block lies between fuzzification and defuzzification blocks. Fuzzification is the process of converting numerical to fuzzy inputs using fuzzy membership functions. Defuzzification is the process of converting fuzzy to numerical outputs. Center gravity method was used for the defuzzification block. Since enough straightforward to implementation, the inference method used by Musavian, (2013) [12] is used here again.

Table 4(a): within-group rules for G1

I1	I11	O1
MH	H	*Excellent*
L	H	*Very good*
H	M	*Very good*
LM	M	*Good*
H	L	*Fair*
ML	L	*Poor*

Table 4(b): within-group rules for G2

I5 I8 I10	I9	O2
all MH	H	*Excellent*
1L / 2MH	H	*Very good*
two L / one MH	H	*Good*
all L	H	*Good*
all H	M	*Very good*
all M	M	*Good*
one L / one M / one H	M	*Good*
two L / one MH	M	*Fair*
all H	L	*Good*
one L / two H	L	*Fair*
all M	L	*Fair*
one L / two LM	L	*Poor*

If scores for each item is represented by x_i, then the aggregation value for the antecedent of each rule is given by:

$$A_{antecedent} = \min(\mu(x_i)).$$

in which $\mu(x_i)$ is the value of membership function for the input x_i. For example, for the rule as bellow:

if x_1 is low and x_2 is high then …

and $(x_1,x_2)=(5,7.5)$, supposing that membership functions are as the figure 2, then:

$$A_{antecedent} = A(y) = \min\left(\mu_{low}(5), \mu_{high}(7.5)\right).$$
$$= min(0,0.5) = 0.$$

The next step of fuzzy inference is the aggregation of input and output fuzzy sets for each rule. This is accomplished by the min function again:

$$A_{ante,conse} = \min(A_{antecedent}, \mu(y)).$$

in which y is the output variable.

Defuzzification is the last step of a fuzzy system. It is the process of converting fuzzy to scalar output. Center gravity method is used for the defuzzification task:

$$scalar = \frac{\sum yA(y)}{\sum A(y)}.$$

For an assessment task with a huge fuzzy rule set, inference process is to be performed in 2 steps: the first step is to infer using within-group rules and then to infer using between-group rules. Fig. (5) shows a block diagram of these two steps. The total fuzzy inference system consists of two fuzzy inference sub-systems. The first block is the input block and it receives 11 inputs. Each input is a score given to the corresponding item by evaluators. The first block generates three outputs using rules within three groups. We can refer to these inputs as scores of groups. Then these middle scores are considered as the inputs for the output stage. The output stage uses between-groups rules to estimate the final fuzzy score.

Table 4(c): within-group rules for G3

I2	I3	I7	I4	I6	O3
×	H	H	H	H	*Excellent*
H	1M	1H	H	H	*Excellent*
LM	1M	1H	H	H	*Very good*
H	M	M	H	H	*Very good*
LM	M	M	H	H	*Good*
×	1L	1M	H	H	*Good*
×	H	H	1M	1H	*Very good*
×	1M	1H	1M	1H	*Good*
H	H	H	M	M	*Very good*
LM	H	H	M	M	*Good*
H	H	H	1L	1H	*Very good*
LM	H	H	1L	1H	*Good*
×	1M	1H	1L	1MH	*Good*
×	M	M	L	L	*Fair*
H	1L	1H	L	L	*Fair*
ML	L	L	L	L	*Poor*

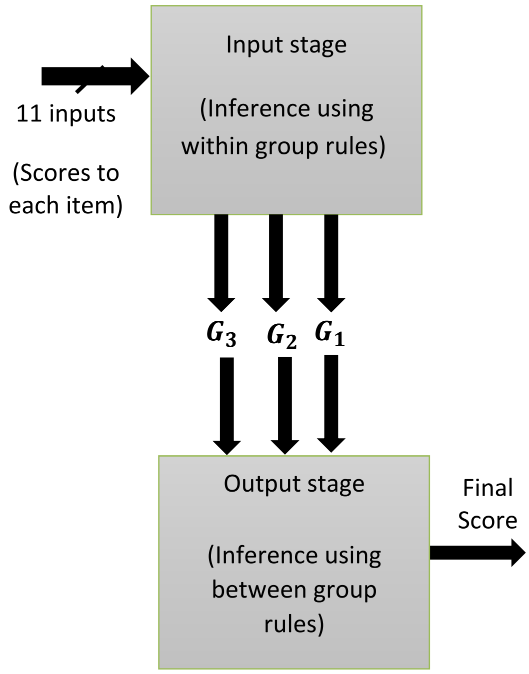

Fig. 5: inference is performed in two stages.

Results and Discussion

As a benchmark for the performance of entire the assessment system, a comparison is made between fuzzy and traditional calculations focusing only on group 1 with two items out of 11 items of assessment. Results are shown in table 6. The same 15 experts were asked to assign a coefficient to each item twice in two months interval between. Each time they were filling up a questionnaire, they assigned different coefficient to items. But when they asked to determine the linguistic descriptive relations between inputs and output (that is the fuzzy rules), the difference was so negligible. Table 6 shows assigned coefficient determined by experts in two inquiries. Also mean and variance values of coefficients for items 1 and 11 (G1) are shown.

Table 5: Mean and variance for coefficients for items 1 and 11 (G1)

Frequencies (first/second time of inquiry)	Item 1	Item 2
1/2	0.5	0.5
3/5	0.4	0.6
4/2	0.3	0.7
1/0	0.6	0.4
5/6	0.2	0.8
1/0	0.1	0.9
Mean/Var.	0.3/0.14	0.7/0.14

Comparing first and second rows in table 7, we will figure it out that a slight change in score of items due to non-uniform assessing, will slightly change the final score. See rows 2 and 3 where only item 1 has been changed. Item1 has a small effect on the final score than item11, therefore we expect a slight change on it, not to change the final score as n.f method did.

Table 6: Final scores using fuzzy and non-fuzzy methods

[item1, item2]	n.f method	Fuzzy method
[5, 5]	5	4.9
[4.7, 4.8]	4.73	4.85
[4.8, 4.8]	4.8	4.85

n.f: non-fuzzy

Conclusion

In this study, a novel method was proposed to determine the score of an activity, a task, or a tool that is designed for learning purposes based on Fuzzy sets and their respective calculations. Fuzzy assessments result in avoidance of the variety of manner of grading by different evaluators. Many studies have been conducted on fuzzy assessment tasks. Usually, an assessment will be performed based on some items and an evaluator gives scores to each of them. Final scores are calculated by aggregating these scores. A serious problem with this scoring mechanism is that giving an exact score (as a number say in the range of 0 and 10) cannot be performed in a certain manner. Therefore, evaluations always depend on evaluators and even the time that an evaluation task is being performed. Fuzzy evaluation makes it possible for an evaluator to choose one option from three or five options to give a (fuzzy) score to an item instead of giving exact numerical scores.

In a fuzzy scoring system, a serious problem will arise if there are many items to be evaluated. This leads to a very large number of fuzzy rules. The method proposed in this study fixes the problem arising from the large number of fuzzy rules.

As mentioned before, we are fixing a serious problem in fuzzy assessment tasks with large number of rules. In previous similar studies, this problem was not the main issue and main efforts was to express the benefits of fuzzy calculations in an assessment task. In our study when looking at final assessment results, and especially when we are dealing with diversity of scores, we can observe that very small variance values are presented by fuzzy method assessment. This means that an assessment by different assessors tends toward a unique score.

A limitation for the proposed method to be implemented is that items of assessment should have the property of being put in a limited number of groups. The smaller number of groups, the easier dealing with the huge rule set.

All fuzzy assessment tasks with large rule set carried out before with limited number of possible rules, are strongly recommended to apply the proposed grouping method for the whole their rule set.

Since the process of dividing rules into groups is the main key to our proposed method, a future study is to apply neuro network pattern recognizers for finding the best solution for rules grouping. This will be a very important step for fuzzy assessment tasks with many items affecting final score.

Author Contributions

The main Idea was started by S.S Musavian. She designed main blocks of fuzzy calculations and wrote the manuscript. F. Ahmadi and S. Norouzi designed experts questionnaires, gathered and prepared data for analyses. A. Taghizadeh cooperated in analyzing results.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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