Fuzzy Logic Based Gregorc Learning Style Model Inference and Statistical Evaluation

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Abstract — *Fuzzy logic-based Gregorc learning style model was developed to determine the learning styles of the students. In the Gregorc learning style model, a four-input and one-out Mamdani-type fuzzy logic algorithm is used to find out which intelligence type belongs to the student in Gregorc learning style. This system is modeled using the fuzzy logic method in Matlab computer software environment and C # programming language is used in the development phase of the model. The research was carried out with 151 students. Gregorc Learning style questionnaire was used to collect the information. The Kolmogorov-Smirnov test was used to determine whether the quantitative variables in the data obtained were suitable for normal distribution. The groups were compared with Mann Whitney U or Kruskal Wallis H test because they did not conform to normal distribution in terms of quantitative variables. Students' learning styles and ages, learning styles and departments, learning styles and grade levels, learning styles and differences between high school types were determined.*

Keywords — *Fuzzy Logic, Gregorc Learning Style, Statistics*

I. INTRODUCTION

Individual differences, different learning and perception abilities, different intelligence levels have attracted the attention of educators from past to present and various researches have been needed on this subject. The concept of individual difference is a concept that is overlooked during the application as well as supporting the professional work of educators and motivating them to develop new methods. There are different studies in the literature on this subject [1]. The concept of learning style is one of the most important concepts that define the individual's maximum learning ability. According to the researchers, determining the learning styles of individuals enables individuals to be more successful in their learning lives and accordingly in their future lives, while it is effective for educators to organize private education experiences for individuals [8,9].

The concept of fuzzy logic It was created by Lotfi Zadeh in the 1960s. Zadeh stated that the vast majority of human thought is not certain, that is, it is blurred. This concept, which creates a new understanding of control, has been used all over the world. Fuzzy logic, which is suitable for the philosophical mindset of the Eastern world, also explains a transition and continuity. In contrast, in classical logic there are two opposite and boundary values of 0 or 1, that is, white or black. But in fuzzy logic, there are intermediate colors such as gray between white and black [5,7]. Fuzzy logic can also be defined as a decision making mechanism for mathematically modeling the behavior of verbal expressions within the imprecise boundaries specified by a specialist. Fuzzy logic is about approximate reasoning rather than fixed and precise. Compared to traditional logic, fuzzy logic variables can have an accuracy value ranging from 0 to 1. The principles of fuzzy logic are expressed as follows [3];

▪ In fuzzy logic, approximate values are used instead of certain values.
▪ For fuzzy logic, information is defined by very little, little, small, large linguistic expressions.
▪In fuzzy logic all values are shown with a membership degree in the range [0-1]
▪ For systems whose mathematical model is very complex and difficult, fuzzy logic is a suitable method.

Fuzzy logic control consists of three basic stages. These are;
▪ Fuzzification
▪ Inference and Knowledge Base
▪ Defuzzification

The basis of the fuzzy logic approach in is to use the inputs created by the linguistic variables derived from membership functions in the decision making process. The membership functions can be used as Gauss, triangle or trapezoid.

The rules set for decision making and inference are found in the rule base. The rules define the logical relationship between the system's input and output values. When defining rules, it is generally defined in the structure of "IF" - "IF".

The output value obtained by the fuzzy inference mechanism is the fuzzy set. The process of converting this output back into sharp value is called rinsing and the unit performing it is called rinsing. Different methods are used in the literature for rinsing. The most commonly used methods are center of gravity, average of weight and maximum rinsing methods [5].

Based on the Fuzzy Logic technique developed by Yamaichi Securities in 1988, the expert system informed the signals of the crisis experienced in the Black Market named Tokyo Stock Market eighteen days in advance. After this successful result, interest in fuzzy logic increased and Laboratory for Interchange Fuzzy Engineering (LIFE) laboratories were established in mid-1989 by 51 companies such as SGS, Thomson, Omron, Hitachi, NCR, IBM, Toshiba and Matsuhita to create an international working commission [4]. There are similar studies about our subject in the literature. In the study called "Fuzzy Grading System", the researchers worked on the computer system evaluating the notes using fuzzy logic. In the study, fuzzy notes with three entries of the system, fuzzy vectors of teacher performance and the effect of student grades on the system and the boundary values obtained as a result of the simulation process were examined [5]. In their study, Kazu and Özdemir aimed to use the artificial intelligence technologies to take into account individual differences using the fuzzy logic model [6].

In this study, the software developed using the Gregorc learning style model with a fuzzy logic approach was used [2]. With this software, it is aimed that the student knows the learning style model and the student can reach the information more quickly and save time and achieve success. User interface and C # programming language and MATLAB system were used in the development of Gregorc learning style model [2].

II. MATERIAL AND METHODS

The following steps were followed in the realization of our study.

A. Developed System

In the fuzzy logic based inference system developed to determine the best learning style of the individual, the users are given information about the use of the system after opening the initial interface when they first enter the system. The user is then expected to score the specified questions. The answers given by the user are taken as input data by fuzzy logic, which is the system running in the background, and the user can learn the most appropriate learning style and level by applying the steps of, rule-based inference and rinsing on these input data.

In this study, a designed initial interface (figüre 1) and interface containing 20 questions compatible with Gregorc learning style was applied to students [2]. The students participated in each question by giving 1, 2 or 3 points and 1 LOW, 2 MEDIUM and 3 points were determined as HIGH. According to the students' scores, the choice of learning style that was appropriate for them was determined through the fuzzy logic based system. C # program software language was used to determine the Gregorc learning style model.

From these questions prepared;

- The total score of the 1.-5.-9.-13.-17th questions measures whether there is a CONCRETE RANDOM Learning Style is dominant,
- The total score of the 2.-6.-10.-14.-18th questions measures whether there is a CONCRETE SEQUENTIAL Learning Style is dominant,
- The total score of the 3.-7.-11.-15.-19th questions measures whether there is an ABSTRACT RANDOM Learning Style is dominant,
- The total score of the 4.-8.-12.-16.-20th questions measures whether the ABSTRACT SEQUENTIAL Learning Style is dominant.

If the total of the points given by the user individuals to the questions is between 5 and 7 values for each feature, it is defined as "LOW", between 8 and 12 values as "MEDIUM" and between 13 and 15 values as "HIGH". Thus, the individual determines the most appropriate learning style and level.

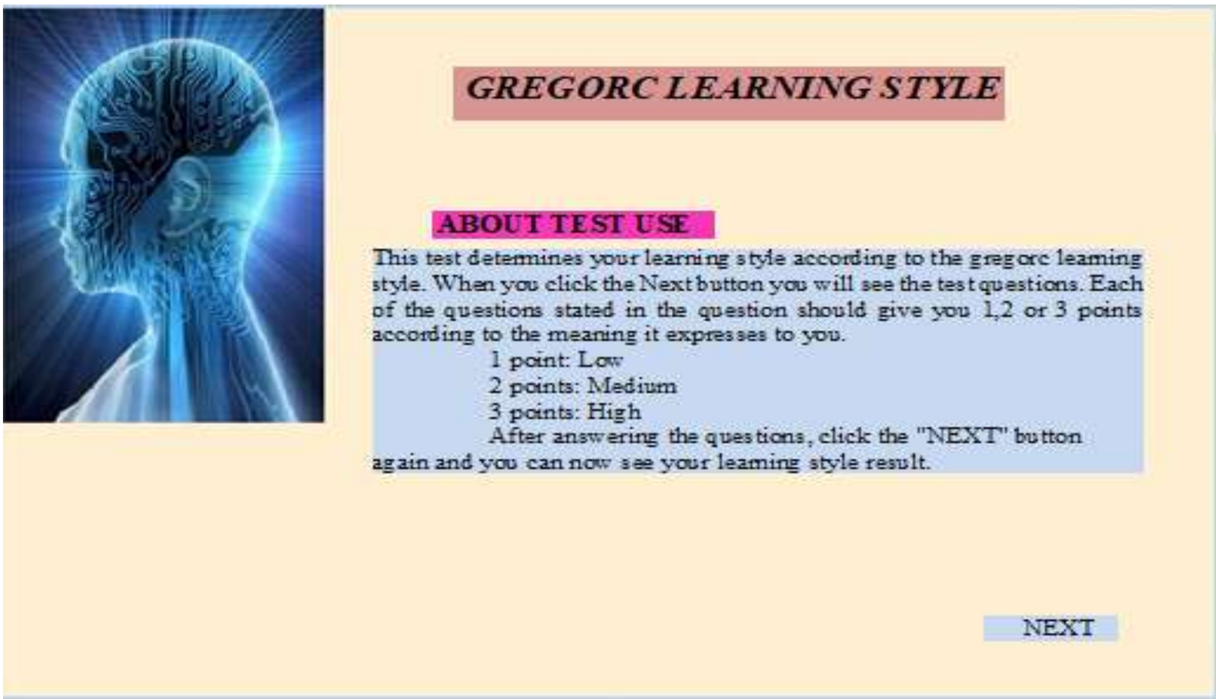

Fig. 1 Initial Interface of Gregorc Learning Style Test

B. Data analysis

It was used in MATLAB 2014 program in the demonstration of the rule base and membership functions during the blur phase. A questionnaire was applied on the students and the data obtained were entered into the fuzzy logic based inference system. SPSS 22.0 package program (Statistical Package for Social Sciences) was used to evaluate the questionnaire. The data obtained from the Gregorc Learning Style Preference Questionnaire were processed into SPSS data entry pages and analysis was performed using appropriate statistical methods according to the types of data groups. Whether quantitative variables are suitable for normal distribution was examined with Kolmogorov-Smirnov test. The groups were compared with Mann Whitney U or Kruskal Wallis H test since they did not conform to normal distribution in terms of quantitative variables. The relationship between quantitative variables was examined by Spearman correlation analysis. Descriptive statistics of quantitative variables were shown as mean ± standard deviation or median (25-75th percentile). Descriptive statistics of qualitative variables were expressed as frequency (%). $p < 0.05$ values were considered statistically significant.

III. FINDINGS

A. Findings And Comments On Students' Learnıng Styles

According to the scores obtained from the Evaluation of Students 'Views on Gregorc Learning Style Model Questionnaire, it was investigated what their preferences regarding learning style are and whether there is a difference between these students' learning styles. Frequencies and percentages related to the departments, classes and high school type of students are calculated.

TABLE I. Frequency and Percentage Values Regarding Demographic Features

Variable		**N** (frequency)	**%**
Section	Construction	43	28.5
	Motor Vehicles	63	41.7
	Installation	36	23.8
	Automotive	9	6.00
High School Type	Technique	56	37.1
	Vocational	95	62.9
Grade	10th grade	59	39.1
	11th grade	34	22.5
	12th grade	58	38.4

Average ± standard deviation, minimum and maximum values of the learning styles in the Questionnaire for Evaluation of Students' Views Regarding Gregorc Learning Style Model are given in Table 2.

TABLE I. Descriptive Statistics on Learning Styles

Descriptive Statistics	**Learning Styles**			
	Concrete Random	**Concrete Sequential**	**Abstract Random**	**Abstract Sequential**
$\bar{X}$ + SD	10.97±2.66	11.05±2.65	11.41±2.97	10.95±1.98
Min.	5	5	5	6
Max.	31	31	31	15

$\bar{X}$: Average SD: Standard Deviation
Min.: Minimum Max.: Maximum

B. Findings and Comments on the Differences Between Learning Styles of Students According to Age Groups

When there was a significant relationship between the age groups and learning style preference scores of the students, it was determined that there was a negative and significant relationship between the age groups' concrete random, abstract random and abstract sequential preference scores ($p < 0.05$).

TABLE III. The Relationship Between Students' Age Groups and Learning Style Preference Scores.

	Concrete Random	**Concrete Sequential**	**Abstract Random**	**Abstract Sequential**
Age	r=-0.192 **p=0.018**	r=0.151 p=0.065	r=0.170 **p=0.036**	r=0.202 **p=0.013**

r: correlation coefficient p: probability value

C. Findings and Comments on the Difference Between the Learning Styles of the Students According to Their Departmental Status

The sections of the students in the Vocational and Technical Anatolian High School that are evaluated are divided into 4 sections as Construction, Motor Vehicles, Installation and Automotive.

TABLE IV. The Relationship Between Students' Departments and Learning Style Preference Scores. X^2: Chi-square test statistics, sd: Degree of freedom

Learning Style	DEPARTMENTS				X^2	sd	p
	Construction (n=43)	Motor Veicles (n=63)	Installation (n=36)	Automotive (n=9)			
Concrete Random	11(9-13)[ab]	11(10-13)[a]	10(9-11,75)[b]	11(10-11)[ab]	8,584	3	0,035
Concrete sequential	11(10-12)[ab]	12(10-13)[a]	10(8-12)[b]	11(9-13)[ab]	9,262	3	0,026
Astract Random	11(10-13)	11(10-13)	11(9-12)	11(10,50-13)	2,203	3	0,531
Concrete sequential	11(10-12)	11(10-13)	11(9,25-12)	9(8-12,5)	4,751	3	0,191

In order to determine whether there is a significant difference between the learning styles according to these sections, the Kruskal Wallis H test was performed since the scores they received according to the learning styles did not conform to the normal distribution. Descriptive statistics about the learning style preference scores of the students are given as median (25th-75th percentile). Accordingly, while the random random and abstract sequential scores do not differ according to the sections ($p > 0.05$), it was determined that the concrete random and concrete sequential scores differ significantly according to the sections ($p < 0.05$). When the scores of both concrete random and concrete sequential learning types are examined, it is seen in the Table 4. that the scores of the students in the Motor Vehicles section are significantly higher than the students in the Installation section.

D. Findings and Comments on the Differences between Learning Styles of Students According to High School Types

The findings of whether there is a significant difference between the learning styles of the students according to high school type were examined as Vocational High School and Technical High School. In order to determine whether there is a significant difference between the learning styles of the students in this school according to their high school types, the Mann Whitney U test was performed since the scores they received according to the learning styles did not conform to the normal distribution.

Descriptive statistics of students' learning style preference scores according to high school type are given as median (25th-75th percentile). Accordingly, it was determined that learning styles were not significantly different among high school types ($p > 0.05$).

TABLE V. Descriptive Statistics and Comparison Results of Learning Style Preference Scores According to High School Type

Learning Style	HIGH SCHOOL TYPE		U	P
	Technical	Vocational		
Concrete Random	11 (10-12)	11 (10-12)	2485	0,495
Concrete Random	11(9,25-13)	11 (10-13)	2531	0,615
Concrete Random	11 (10-13)	11 (10-13)	2526	0,602
Concrete Random	11 (10-13)	11 (9-12)	2311	0,174

U: Mann Whitney U test statistics P: probability value

E. Findings and Comments on the Difference Between the Learning Styles of the Students According to the Grade Level

Kruskal Wallis H test was used to determine whether there was a significant difference between the learning styles according to the grade level of the students and the scores they received according to the learning styles did not correspond to the normal distribution. Descriptive statistics regarding the learning style preference scores of the students according to their grade level are given in the median (25th-75th percentile).

TABLE VI. Descriptive Statistics and Comparison Results of Learning Style Preference Scores According to Grade Level

Learning Style	Class			X^2	SD	P
	10th (n=59)	11th (n=34)	12th (n=58)			
Concrete Random	11 (10-13)	11 (9-12,25)	10 (9-11,25)	5,783	2	0,550
Concrete Random	12 (10-13)	11 (10-12,25)	11 (9-13)	5,028	2	0,081
Concrete Random	12 (10-13)	11 (9,75-12)	11 (9-13)	2,686	2	0,210
Concrete Random	11 (10-13)[a]	11 (10-12,25)[ab]	10,50 (9-12)[b]	6,793	2	**0,031**

SD:Standart Deviation P:Probability Value

According to the Table 6., while concrete random, concrete sequential and abstract random scores do not differ according to class status ($p > 0.05$), it was determined that abstract random scores differ significantly according to classes ($p < 0.05$). When the scores related to the abstract sequential learning type are examined, it is seen that the scores of 10th grade students are significantly higher than the scores of 12th grade students.

IV. CONCLUSIONS

Learning style is a way that the individual follows in perceiving, processing and using information. The individual who is aware of the learning style, how student learns, recognizes own learning ways and can easily guide own learning. In order to ensure that a material to be learned is comprehended by all students at the same level and quality, presenting the subject to be learned with methods and techniques suitable for different learning styles facilitates understanding of the subject and affects the permanence of learning in the individual. It is wrong to determine the learning style of the student with certain expressions and to conclude that he learned with a single learning style. The individual can have many learning styles in certain proportions. Fuzzy logic algorithms and learning styles are much more flexible than getting stuck between exact lines. In this way, individuals' learning styles will be determined and the individual will learn more effectively. Within the scope of this study, the fuzzy logic based Gregorc Learning Style Preference Questionnaire system containing 20 questions was developed and the data obtained were analyzed using the SPSS 22 program. Learning styles of students in Vocational and Technical Anatolian High School were tried to be determined according to Gregorc Learning Style Model. Gregorc Learning Style Preference Questionnaire was applied to 151 students.

When the results obtained in the analysis of the obtained data are examined, it is seen that the dominant learning style of the students is Abstract Random. The ages of the students are in the range of 16, 17, 18 and according to the Table 3., it is seen that as the age of the students increases, their score on the Gregorc learning style scale decreases. According to Gregorc learning style, it has been determined that students' learning style has a negative and significant relationship between age, concrete random, abstract random and abstract sequential preference scores.

It was determined that the students' education was not different according to the departments, while the abstract random and abstract sequential scores did not differ according to the departments. When the scores related to the learning types are analyzed, the scores given by the students in the Motor Vehicles section are significantly higher than the points given by the students in the Installation section for both concrete random and concrete sequential learning styles.

Within the scope of the study, the scores given by the 10th, 11th and 12th grade students were examined, and the scores of the 10th grade students related to the abstract successive learning type were significantly higher than the 12th grade students' scores. The scores given by students to the questions of concrete random, concrete sequential and abstract random learning style do not differ according to grade level. When students are analyzed by Technical High School and Vocational High School type, it is seen that the learning styles related to learning style preference scores are not significantly different.

Each individual has its own biological and physiological developmental features. These differences affect people's understanding and perception of knowledge and skills differently in the education process. Educators acknowledge that each student has a different way of receiving information. Research shows that using fuzzy logic-based approaches gives more accurate results than traditional methods and techniques. This situation will increase the quality of the students' learning and will be a factor that positively affects both the success of the school and its success in the life process.

With the fuzzy logic-based system developed in the scope of the study, it has been determined that instead of having a definite learning style as in classical logic, the student can have many different learning styles by rating approximately. Thus, learning style determination process has been modeled more realistically with fuzzy logic method.

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