IJICTR
International Journal of Information & Communication Technology Research

Volume 12- Number 1 – Winter 2020 (56 -67)

Identify Learning Style Using a Fuzzy System Based on Network Behaviors

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Received: 10 August 2019 - Accepted: 7 December 2019

Abstract—**In the e-learning environment, there are various learners with varying learning characteristics, including prior knowledge, experience, motivation, and learning objective, and each learner is responsible for their own learning. In such environments, there would not be an effective and efficient learning, unless adaptive approaches are considered. Thus, the ultimate goal of adaptive learning is delivering courses, programs, and educational resources tailored to the learning characteristics of individual learner. The most important step in adaptive learning is to identify and select appropriate indicator based on which adapt learning would be performed. Researchers have selected a variety of indicators in their studies, and due to the fact that learning style model is one of the most significant indicators in recognizing individual differences in the learning process in order to adapt to the e-learning environment, in this study, "Kolb's learning style model" was considered as the selected indicator. However, given the fact that there is uncertainty in determining this indicator, it is very complex, thus it cannot accurately described and defined. In this research, fuzzy sets theory was used to model the uncertainty and inherent ambiguity in the learning style model by creating a set of rules which was able to increase the precision of identifying dimensions of the learning style. To achieve this, a fuzzy system utilizing learners' network behaviors in the environment to identifying and modeling their learning style was designed. In this system, the precision of the measurement in identifying individuals' learning style compared to the results of the questionnaire that was previously completed by learners is 89.07%, showing that this method has increased the precision compared to other methods.**

Keywords- E-Learning; Adaptive Learning; Kolb's Learning Style Model; Fuzzy System; Identifier Learning style

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I. INTRODUCTION

Learners may enjoy different prior knowledge, experience, goal and motivation in an e-learning environment, and without adaptive approaches, no Effective learning will occur for learning [1].
Hence, the ultimate goal in adaptive learning is to provide courses and educational content tailored to the specific characteristics of each learner [2- 4].
Learning adaptation in systems comprises three aspects: the adapted form of content presentation, sequencing of presentation, and adapted navigation tools [2].

A. Content Presentation Format Adaptation

In presentation format adaptation, course content presentation is commensurate with the learners' characteristics throughout the learning process. The purpose of this adaptation is to adapt the type of presentation medium and concept and information transfer to the learners' abilities, preferences, and interests, so as to enhance the learners' quality and speed in the learning process. "Arthur" is one of these adaptive learning environments. In a typical learning environment, there is one teacher and several learners. Arthur attempts to deliver adaptive learning by gathering lessons from a group of teachers for each learner. Consequently, in this system, the "one-to-many" relationship of the typical learning environment has become the "many-to-one" relationship to improve the learning environment [5].

B. Presentation Sequencing Adaptation

In sequencing, the presentation of educational content, the order in which the content is presented to the learner is adapted according to his/her characteristics, abilities, and learning style. Here, the problem is not the conceptual order but the order of the learning objects and the lesson that affects the quality of learning. The "INSPIRE" network is an example of such systems that determines the order in which the learning objects are presented to a learner in interacting with the learner based on his/her learning style and background knowledge [6].

C. Navigation Tools Adaptation

This type of adaptation seeks to support learners in circulating, orienting, and achieving within-network learning based on their needs and habits. The AES-CS is an example of such systems that adapt different aspects of the learning process based on the cognitive style of learners [7].

In this research, adaptation in learning aims at the first aspect and seeks to be able to adapt the form of content presentation in the environment based on the characteristics of the learners. The important step in adaptive learning, for adaption program and educational content according to the learner's characteristics and needs is that to know what individual characteristics should be considered as an effective index of learning. Researchers have selected a variety of indicators over the years 2002–2019, such as behavioral, personality, and learning style model. Review of literature shows that the use of learning style models is more than the other indicators in the research works models [8-22].

The term learning style was first coined in 1954 by Herb Thelen. Different definitions for learning style have been told, and there isn't specific definition for that. One of these definitions is: learning style is his/her way of learning along life which he/she use of them especially in most of situations. In fact, learning style is description of behavior and point of view that determine preferential learning style of learner [23].

Reifova, consider learning style as the way of learning, understanding and processing information. Learners use of different ways along period of learning, for example maybe some of learners are learnt better along activity in different groups, while another prefer to be alone. Learning style surveys recognition learners' preferences in the way of presentation of learning content, the way if working with learning content and how to be interaction with information [23-24].

Sensitivity of learner to different shapes of information and learning environment, will show learning style. It should considered that each learner has specific method of learning along learning process. Learning style model is one of the most important criteria for recognizing any individual differences in learning process in order to create adaptation in e-learning environment, and has a lot of advantages including: identifying learners' strengths and weaknesses, improving satisfaction, increase learning speed, improving the quality and efficiency of learners' learning process in the network [23-24].

Identify learning style in addition to being enlightened by the learners' strengths and weaknesses, it creates a kind of self-care in learning, and it brings better choices to the learner and it can help the instructor to present suitable guides according to learners' learning style and consequently increase learners' confident to learning network [23-25].

There are many approaches to measure the learning style models that can be applied to several theories like Felder and Silverman [26], Kolb [27], Meyers Briggs [28].

A common method of measuring learning style is using a questionnaire, which has two main problems: One is the disruption of the training process (because the person has to answer it during the training process), and the second is the uncertainty of the answers (because the person may provide unrealistic answers to the questions). One of the new approaches in this field is to identify learning style model using network behaviors; they are implicit and have no intervention with the learning process, in addition, since they use the learners' actual behaviors in the network, the answers are correct [24].

In this study the learning style model is "Kolb's learning style". We designed the method based on the network behaviors for identifying the learning style of learners. The structure of the paper is as follows: Section 2, introduces the Kolb's learning style model. Section 3 describes the proposed method for measuring this indicator by the fuzzy sets theory. Section 4 describes the system are designed to identify the style. Section 5, the designed system is tested on a number of e-learners and the results are compared by the results of the questionnaire in order to validate the efficiency of the new system. Finally, section 6 is devoted to research conclusion.

II. KOLB'S LEARNING STYLE

For Kolb, learning is the process that transforms the experience to knowledge. This learning style model is based on the Experiential Learning Theory (ELT), where experience is considered as the source of learning. Instead of emphasizing teacher-centered learning, the experience focuses on learning through personal experience [27].

In recent decades learning theories despite emphasize on behavior, survey human's experiences and unique nature of man in the world. In experiential learning theory, experience is considered as source of learning and development. The term experiential is to distinguish this theory from behavioral learning theories which ignores the role of mental experience in learning process and cognitive learning theories that emphasizes learning over emotions, are applied [27].

The reason of choosing the Kolb's style model in the proposed method is that in this theory, experience learning is a dynamic perspective of learning based on four- stages cycle in learning which simulates brain function and Since, in this research network behaviors that are performed dynamically in the network by learners are based, Kolb's learning style model is considered more appropriate choice.

As mentioned in experiential learning, learning style is considered as the dynamic psychological attribute, that being influenced by the four stages of the learning cycle, including concrete experience (feeling), abstract conceptualization (thinking), active experimentation (doing), reflective observation (observation) [27].

A. Concrete experience (feeling)

It is achieved through growth of feeling, when the person undergoes specific experiences and becomes involved with the subject. So the learner floats in trouble and relies more on one's feel than one's logic. At this point, the person does what he/she feels is right and often acts on the basis of feeling when attempting to do the same.

B. Abstract conceptualization (thinking)

Learning at this stage involves problem analysis and rational thinking in order to create future theories. This phase depends on logical thinking, modeling, and the development of assumptions to test the next stage.

C. Active experimentation (doing)

Learning at this stage involves the use of thoughts and ideas, and it is done through trial and error. Clearly, this has led to a series of experiences from which emotions arise, and the cycle continues.

D. Reflective observation (observation)

Includes attention to past experiences, seeing and hearing before acts. Therefore, experiences and feelings must be given special attention to formulate experiences.

This cycle focuses on ways based on which learners acquire different experiences or convert them from a form to another. These four stages of the learning cycle form two perpendicular dimensions: 1) acquiring information through experience, which consists of two stages of concrete experience and abstract conceptualization, and 2) conversion (i.e., processing of received information), which consists of two stages reflective observation and active experimentation. These two orthogonal dimensions create four spaces (or contexts) in the learning cycle that are filled with four groups, namely the Assimilating, Converging, Accommodating, and Diverging knowledge. The Kolb's learning cycle is illustrated in Figure 1[27].

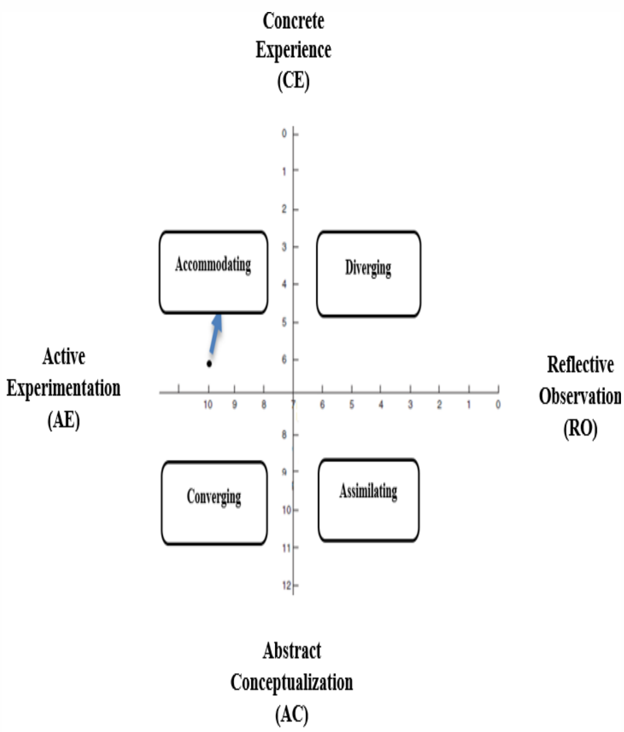


Figure 1. Kolb's learning style model [27]

Kolb designed a questionnaire consisting of 12 items for determining the learning style of learners. Each item suggests four-sentences that rank the learners from 1 (not all true for me) to 4 (very true for me). The first choice of questions is about learning through "feeling", the second choice is about learning through "observation", the third choice is about learning through "thinking", and the fourth choice of questions is about learning through "doing" [27].

The total scores of each four-sentences in the 12 items, identify how to learn the learner. The difference of (AE – RO) and (AC – CE) gives two new scores. These two scores are two coordinates of Figure 1 and determine the learners' learning styles. This format differs from the standard format because it has been formulated by experiential learning theory and is a "forced choice format" that ranks the individual's relative preferences between the four groups of Kolb's learning cycle. However, some learners do not fall into four groups and are located at the boundary between groups [27].

Here, a number of learners fall into none of the four groups of Converging, Diverging, Assimilating, and Accommodating; rather, they lie on the boundary between the four quadrants and the certainly cannot be considered one of the four groups mentioned. In this research, the use of the fuzzy sets method is proposed for solving the existing problem. This method can well model the created uncertainty considering the other four groups. It further can show the membership function learner to an existing group, and to solve the two major problems of the questionnaire. (I.e. disruption of the learning process and uncertainty of the answers), and the learners' network behaviors were used to measure the learners' learning style. Because in this case, based on the real behaviors of the learner in environment, it will be determined learners' learning style, and the error rate will decrease [27].

Learning style is one of the topics that deals with living things, and for this reason, it is not possible to define an exact and explicit boundary for it. This is categorized into issues with inaccurate boundaries. In other words, as has been observed, there are learners who do not necessarily belong to any of the groups, and here we are dealing with fuzzy sets. In crisp sets, the elements are members of the sets or not. While in fuzzy sets, there are elements that are partly members of the set. In the next section, fuzzy sets will be examined in details.

III. METHOD

Different methods have been used to identify learners' styles in e-learning environment, and adaptive learning. One of the methods is the Naive Bayes. Naive Bayes is a probability-based approach to inference. The basis of this method is that, a probability distribution for any quantity. Which can be optimized by observing a new data and arguing about its probability distribution. An important advantage of this method is its strong theoretical basis and the most important disadvantages, is the assumption of conditional independence of the properties of the patterns from one another. Another disadvantage is the need for relatively large training data that is costly and challenging. In the studies [29-32] of this method has been used to identify learners' learning style.

Because learners learn in a variety of ways, by focusing on different types of information and processing techniques, one of the desirable features of an e-learning environment is that all learners can learn well despite their different learning styles [29].

Determining how learners learn, and in other words, what learning styles they have, Garcia 2007 has been described by a Bayesian Network to identify learners' learning styles. Selected variables include Felder-Silverman learning style model dimensions and determinant factors of these dimensions that were extracted from the learners' interaction in the network [29].

Another study aimed at identifying learners' learning styles and providing content and curriculum tailored to learners' learning styles, utilized a dynamic Bayesian Network [30]. There are three types of variables in this network:

a. Variables representing the learning style: Each dimension of the Felder-Silverman learning style model: perception, input, processing and understanding, is modeled with a variable in the network, that each variable can also accept a set of values. For example, the variable representing the input dimension can have one of two visual and auditory values.

b. Variables representing the selective learning objects: For learning objects, there are also variables in the network that include the format learning object (text, image, video, audio, etc.), type of selective learning source (practice, Q&A, simulation, test, lecture, etc.), level of interaction with the learning network (very low, low, medium, high, very high), type of interaction and reactions in the network (active, indifferent, Hybrid).

c. Variables representing the learners' ranking of the selective learning objects by the network: The learner can rank from one to four the selected learning object.

Based on the relationships between the defined variables, the learning style of the learner is identified and appropriate learning objects is presented.

The disadvantage of this approach compared to other automated approaches to identifying learners' learning style is that the network, input is extracted the learner himself is asked through a questionnaire [30].

The Decision Tree method is another method used to identify learners' learning style. This method uses the concept of tree in artificial intelligence to represent different concepts and is used to approximate objective functions with discrete values. This method is one of the most popular inductive learning algorithms. The Decision Tree method provides a tool for extracting rules from numerical and symbolic data. The set of rules formulated in the Decision Tree makes it possible to accurately decide on the new data classification. The Decision Tree method has also been used to identify learners' learning style [33-35].

The advantages of the Decision Tree method can be easily understood, noise resistance of input data, ability to categorize large and complex data, reusability and combinability with other methods. The most important disadvantage of this method is that the tree exponentially grows if the problem data grows and expands. Therefore, it is not possible to use this method computationally if the number of features considered is increased. As the learning attribute space and the number of attributes is extensive, using the Decision Tree is not an appropriate choice. However, in some studies for learner modeling, this method has been used. The definite logic and inflexibility of this method disables to modeling and identifying learners' learning styles [33-35].

Another method to identify learners' learning style, is that Soft Computing methods such as Artificial Neural Network (ANN). The Artificial Neural Network has been used to identify learners' learning styles in studies. Latham 2013, two dimensions of processing and understanding of Felder-Silverman style model are identified. In this research, we first select a subset of the properties of two dimensions from a set with 41 properties, and then, the network is trained to identify learners' learning style based on selected features and using train data. Artificial Neural Networks have been successful in improving the accuracy of identifying learning styles with relatively small datasets [36-37].

Many real-world information is uncertain and ambiguous. One of the methods of modeling uncertainty and ambiguity is fuzzy theory. Fuzzy sets theory was developed on the basis that the essential elements in human thinking are not exact quantities, but linguistic vocabulary associated with uncertainties such as good, low, or high. Fuzzy sets theory is able to modeling many concepts, variables, and systems that are uncertain and ambiguous, and provide the basis for reasoning, inference and decision making in uncertain terms. In the fuzzy sets theory, each member of the set has a membership function $\mu_X(A)$ as follows [38]:

$$0 \leq \mu_X(A) \leq 1 \tag{1}$$

The learning style of the learner is also one of the uncertainties that we want to model here using this method. As noted, some learners have not been identified learning style and lie on the boundary between the four group by the Kolb's style questionnaire and cannot classified as one of four groups. Hence the use of fuzzy sets theory can be effective. This theory uses the "if-then" rules to infer. These rules are defined using fuzzy sets. Fuzzy systems combining "fuzzy theory" and "fuzzy logic" provide a framework for expressing the uncertainty in expert knowledge. Fuzzy logic-based systems include four main components: fuzzifier, knowledge base, inference engine, and defuzzifier [38-39].

A. Fuzzifier

In this process, the relationships between inputs and linguistic variables are defined using membership functions. The input variables are indeed converted to fuzzy numbers through this unit. Fuzzy numbers are generalizable real numbers without a single value dependent on a set of values, each with a weight between 0 and 1. Here, the weight is the same as the membership function. Triangular and trapezoidal fuzzy numbers are among the most commonly used fuzzy numbers; the triangular fuzzy number is denoted by the triad A = (a1, a2, a3), where the relation $a_1 < a_2 < a_3$ holds. The membership function of the triangular number is defined as follows:

$$\mu_X(A) = \begin{cases} 0 & \mathrm{x} \leq a_1 \\ \frac{x-a_1}{a_2-a_1} & a_1 \leq \mathrm{x} \leq a_2 \\ \frac{x-a_3}{a_2-a_3} & a_2 \leq x \leq a_3 \\ 0 & a_3 \leq x \end{cases} \tag{2}$$

The trapezoidal fuzzy number is the closest way of displaying expert proposition. Considering$a_1 < a_2 < a_3 < a_4$, the trapezoidal membership function is defined as follows:

$$\mu_X(A) = \begin{cases} \frac{x-a_1}{a_2-a_1} & a_1 \leq x \leq a_2 \\ 1 & a_2 \leq x \leq a_3 \\ \frac{x-a_4}{a_3-a_4} & a_3 \leq x \leq a_4 \\ 0 & a_4 \leq x \end{cases} \tag{3}$$

B.Knowledge Base

This base is made up of a pool of expert knowledge in the form of a set of rules for linguistic variables. These rules describe the relationship between input and output fuzzy sets. Since the type of expert knowledge is primarily expressed in conditional sentences, the knowledge base is essentially a set of “if-then” rules.

C. Inference Engine

This part of the fuzzy system is the brain of the system that acts as the decision-maker and can infer the outputs based on the rules in the fuzzy rules and operators base. In other words, it combines the min and max operators, extracts the fuzzy output from the input fuzzy sets and the existing fuzzy relations, and simulates the human decision-making capability using it. There are various types of mechanisms and inference engines, including Mamdani and Sugeno inference engines.

D. Defuzzifier

This part of the fuzzy system converts the fuzzy output of the inference engine to a definite value. In other words, it works as opposed to a fuzzifier. There are various defuzzifiers, including mean centers, maximum, and center of gravity.

In this section, a fuzzy system is designed in order to determine the learning style of the learners using network behaviors. The fuzzy system components are shows in Figure 2, the following describes the components of the system.

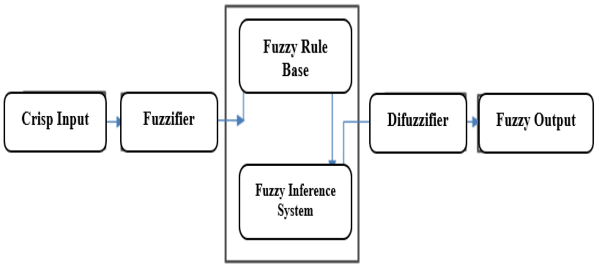


Figure 2. Fuzzy system components [40]

In the next section, the components of the designed fuzzy system are described.

IV. FUZZY LEARNING STYLE IDENTIFIER

A. Fuzzy system input variables

The fuzzy system input variables are learner behaviors. To this end, we first extracted the behaviors and characteristics of Kolb's learning style model. Then, a questionnaire was designed to extract the opinions of the experts in which they were asked to determine the degree of correspondence of the learning behaviors and characteristics with different types of Kolb's learning style model. To analyze the results of the questionnaire, first the numbers 1 to 5 are assigned to each of the very low, low, medium, high and very high answers, and then using the binomial test at the error level of 0.05, the behaviors shown in Table 1 have been identified as behaviors corresponding to the dimensions of the Kolb's model.

It should be noted that there are several behaviors according to the types of networks, and here we try to target network behaviors related to learning environments. Extracted network behaviors has been validated and verified according to the opinions of 10 of the experts in the field of education at Tarbiat Modares University, Allameh Tabataba'i University, and Kharazmi University. The questionnaire was provided to the experts and they were asked to determine the degree of coordination of the types of network behaviors with the behaviors corresponding to the types of styles to be corrected accordingly. Given the number of experts and the CVR standard, the network behaviors of table 1 are acceptable.

Now, after extracting the networking behaviors, these behaviors should be measured in the e-learning environment. Table 1 shows the correlation between the behaviors of various Kolb's learning styles and network behaviors [37].

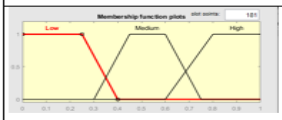
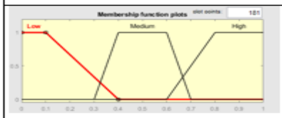
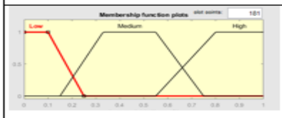
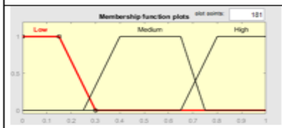
TABLE I. CORRELATION OF THE BEHAVIORS OF EACH KOLB'S LEARNING STYLE WITH THE LEARNERS' NETWORK BEHAVIORS

Network behaviors	Behaviors corresponding to the learning style	Learning style
Sum of observation time intervals practical learning objects and real-world examples until another event recording	Willingness for practical concepts and real-world examples	Converging
Number of recorded observations of difficult exercises	The level of difficulty in selected exercises	
Sum of observation time intervals textual learning objects until another event recording	Willingness to use contextual educational content	
Ratio of the number of individual projects and exercises to the total number of exercises and projects assigned to learner	Willingness to perform individual tasks	
Number of views and posts in forums	Participate in discussion groups	Diverging
Sum of observation time intervals video learning objects until another event recording	Willingness to use video educational content	
Number of views related topics	Willingness to search for relevant topics	
Ratio of the number of group projects and exercises to the total number of exercises and projects assigned to learner	Willingness to do group exercise	
Sum of the time intervals allocated to abstract lessons until another event recording	willingness to apply a deductive teaching method	
Sum of observation time intervals - theoretical and impractical learning objects until another event recording	Willingness for the theoretical and impractical concepts	Assimilating
Sum of observation time intervals video learning objects until another event recording	Willingness to use video educational content	
Ratio of the number of individual projects and exercises to the total number of exercises	Willingness to do individual homework	

and projects assigned to learner		
Sum of the time intervals allocated to the concrete learning objects until another event recording	willingness to apply an inductive teaching method	
Sum of observation time intervals theoretical examples until another event recording	Willingness to read theoretical examples (not practical)	
Number of views and posts in forums	Participate in discussion groups	**Accommodating**
Sum of observation time intervals practical learning objects and real-world examples until another event recording	Willingness for practical concepts and real-world examples	
Sum of observation time intervals audio learning objects until another event recording	Willingness to use audio educational content	
Ratio of the number of group projects and exercises to the total number of exercises and projects assigned to learner	Willingness to do group exercise	
Number of recorded examples	Number of examples to study	

Since experts use linguistic constraints such as low, medium, and high to express the rules related to these behaviors and characteristics that are considered as input variables, fuzzy modeling can be used to define and model them fuzzy. The membership function of linguistic variables is expressed using fuzzy numbers. Since the trapezoidal numbers are closer to the expert opinions [38], these fuzzy numbers are used here. Table 2 shows the definition of three variables "low," "medium," and "high" for learner networking behaviors:

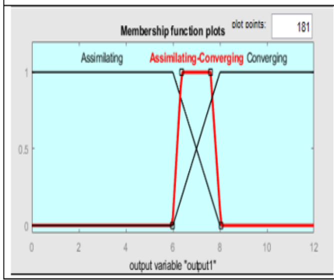
TABLE II. MODELING NETWORK BEHAVIORS USING FUZZY SETS

	linguistic variables	Numerical range	Behavior
	Low	(0, 0, 0.25, 0.4)	Tendency to search for related topics
	Medium	(0.3, 0.45, 0.6, 0.75)	
	High	(0.6, 0.8, 1, 1)	
	Low	(0, 0, 0.1, 0.4)	Tendency to do group exercise
	Medium	(0.3, 0.4, 0.6, 0.7)	
	High	(0.6, 0.8, 1, 1)	
	Low	(0, 0, 0.1, 0.25)	Tendency to whole to partial teaching method
	Medium	(0.15, 0.33, 0.55, 0.75)	
	High	(0.55, 0.8, 1, 1)	
	Low	(0, 0, 0.15, 0.3)	Number of studied examples
	Medium	(0.25, 0.4, 0.65, 0.75)	
	High	(0.65, 0.8, 1, 1)	

B. Fuzzy system output variables

The output variable of a fuzzy system is the determination of the learners' learning style based on four Kolb's model categories. Here, too, we use trapezoidal fuzzy numbers to model the uncertainty caused by complete non-affiliation in each quadrant and determine the degree of membership of each learner to each type of learning style. Table 3 shows on output variables of the fuzzy Kolb's learning style Identifier system, namely the numerical range and their shape:

TABLE III. FUZZY SYSTEM OUTPUT VARIABLES OF LEARNING STYLE IDENTIFIER

	Numerical range	Output
	(0, 0, 6, 8)	Assimilating
	(6,7,8,8)	Assimilating and Converging
	6,8,12,12)	Converging

C. Fuzzy system rules

The fuzzy system rules express the relationships between the input and output variables. These rules are among the items of the Kolb's learning style questionnaire and the network behaviors are correlated to each of the Kolb's learning styles that have been extracted from the experts' field. For example:

"If there is a high willingness for practical concepts and real-world examples, a high level of difficulty in selected exercises, a high willingness to use contextual educational content, and a high willingness to perform individual tasks, then the individual is converging."

"If there is a high level of participation in discussion groups, a high willingness to use video educational content; a high willingness to search for relevant topics, a high willingness to do group exercises, and a high willingness to apply a deductive teaching method, then the individual is diverging."

"If there is a high willingness for the theoretical and impractical concepts, a high willingness to use video educational content, a high willingness to do individual homework, a high willingness to apply an inductive teaching method, and a high willingness to read theoretical examples (not practical) examples, then the individual is assimilating."

"If there is a high level of participation in discussion groups, a high willingness for practical concepts and real-world examples; a high willingness to use a lot of audio educational content, a high willingness to do group exercises and a high number of examples to study, then the individual is accommodating."

The rules in the knowledge base should have the following three characteristics [40]:

A. Complete: The set of fuzzy rules is called complete, if there is at least one rule in the rule base for each point in the Universal Set. Here, for each style, a set of all the rules is extracted by experts, so the set of rules is complete.

B. Consistent: The set of fuzzy rules is called consistent, if not found two rules be antecedent is the same and consequent is contradictory. There were no inconsistencies between the opinions of the experts in determining the rules of this system and the opinions of the experts were convergent. So, the set of rules is consistent.

C. Continuous: The set of fuzzy rules is called continuous, if no two neighbor rules are found that their subscription is empty. The continuous condition of set rules is designed by defining this condition as a limitation in the fuzzy toolbox of the MATLAB R2018b simulation software, and each time a new rule is defined, the condition of its continuous with the previous rules is examined. If the continuous condition is not met, the new rule will be removed from the set of rules.

Table 4 shows the number of rules for each Kolb's learning style model based on experts' opinions.

TABLE IV. FUZZY SYSTEM RULES OF LEARNING STYLE IDENTIFIER

Number of rules	Learning style
81	Converging
243	Diverging
243	Assimilating
243	Accommodating

Part of this fuzzy system is shows in Figure 3 in the MATLAB R2018b fuzzy toolbox. It should be noted that the fuzzy inference engine used is Mamdani-type, which uses fuzzy sets as a result and rule. Here, the output of each rule is nonlinear and fuzzy; in addition, its defuzzification method differs from that of other inference engines. By trial and error, the "maximum average" defuzzifier is also used to map the fuzzy set to the absolute set (i.e., defuzzification).

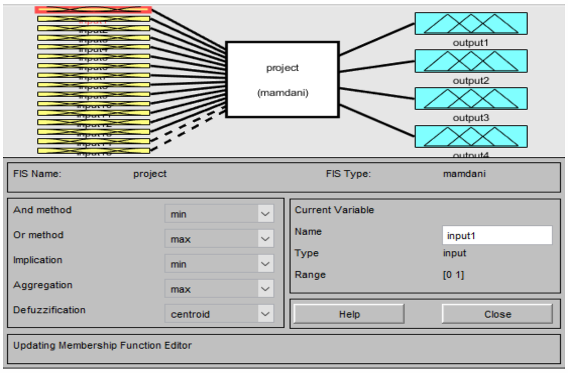


Figure 3. Fuzzy learning style identifier.

It should be noted that in this study, the learner is modeled based on learning style and as stated in the definition of learning style, the learning style of each learner determines how to learning, teaching and the model which based on the content and curriculum to learners presented. Therefore, the fuzzy system designed based on the learner model in an educational process is not independent of the content model and the Tutor model. According to Table 1, network behaviors extracted from behaviors corresponding to different styles are the basis of this system, and in these behaviors, in addition to the learning model, the content model and Tutor model are also considered. These network behaviors have also been used to determine the rules of the system knowledge base and inference engine.

V. EVALUATION

To evaluate the accuracy of the proposed method, we considered 119 students from Al-Aharar High School of (Tehran) Iran that shows information of learners in table 5. These students were first asked to answer the questions on the Kolb's Learning Style Questionnaire. It should be noted that the results of the questionnaire based on research are assumed to be correct (reliability and validity of the results have been proven). After collecting the results of the questionnaire, each learner was instructed according to their learning style in the Moodle Learning Management System.

The Learning Management System used is the Moodle Version 3.7 2018 software package. In this system, learners receive appropriate content based on the learning style. Appropriate content is provided for each learner tailored to the teaching strategies designed to be adapted to their learning needs in the Learning Management System.

An e-learning course of 10th-grade high school mathematics was conducted to analyze the results of the implementation of the system designed in a real environment. Since math is a mental activity, there are many ways to teach and learn it. Additionally, the realization of effective learning and improvement of students' level of knowledge in mathematics is one of the major concerns of teachers. The training course specifications for extracting learners' network behaviors from the environment are shown in Table 6.

TABLE V. INFORMATION OF LEARNERS

Total number of students	Field of study		Grade	Mean Age	Gender
	Experiential sciences	Mathematics			
119	58	61	Tenth High School	16	Female

TABLE VI. SPECIFICATIONS OF THE TRAINING COURSE

Value	Attribute
6	Number of course
3	Number of concepts
29	Number of learning object
2 weeks	Duration
119	Number of participants

During the learning period, the data on the learners' network behaviors in the system were collected and after data collection and conversion using Table 1, the learners' network behavior was measured and considered as the fuzzy system input. Table 7 shows the results of the fuzzy system. As you can see, learners' learning style is well identified through the fuzzy system designed:

TABLE VII. FREQUENCY OF LEARNERS' LEARNING STYLES

Learner	Learning style
57	Diverging
24	Assimilating
26	Accommodating
4	Converging
4	Diverging and Assimilating
1	Converging and Accommodating
1	Central
2	Diverging and Accommodating
119	Total

Then the results of the questionnaire completed by the learners are compared with the results of the fuzzy system based on the data from the network behaviors. The results show that the fuzzy system correctly identified the learning style of learners in %89/07.
Table 8 illustrates this comparison as an example for a number of students from the statistical community. In this table, the values of learners' behaviors from the data collected from the e-learning network are presented in table 1 from left to right, learning style of the learner by Kolb's questionnaire and the fuzzy system.

TABLE VIII. COMPARING THE RESULTS OF FUZZY SYSTEM LEARNING STYLES IDENTIFIER AND KOLB'S LEARNING STYLES QUESTIONNAIRE

Learning style		Values of learner behavior	Learner
System	Questionnaire		
Converging	Converging	(0.9, 0.9, 0.65, 0.8)	1
Converging and Assimilating	Converging	(0, 0.9, 0.65, 0.9)	2
Diverging	Diverging	(0.9, 0.9, 0.9, 0.9)	3
Diverging and Assimilating	Diverging	(0.9, 0.4, 0.9, 0.15, 0.9)	4
Assimilating	Assimilating	(0.8, 0.65, 0.55, 0.9, 0.9)	5
Accommodating	Accommodating	(0.75, 0.7, 0.85, 0.4, 0.85)	6
Diverging	Diverging	(0.75, 0.65, 0.9, 0.4, 0.8)	7

Assimilating	Assimilating	(0.8, 0.70, 0.82, 0.3, 0.91)	8
Converging	Converging	(0.83, 0.55, 0.89, 1)	9
Accommodating	Accommodating	(0.9, 1, 0.56, 0.78, 0.84)	10

As shown table 8, system and questionnaire values are very close together, and comparison of the results showed that the fuzzy system has correctly identified the learning style in 89.07% of the learners' learning styles. In addition to comparing the results of the system with a questionnaire, another important criterion in evaluating the results of a designed fuzzy system is its stability, which ensures the accuracy of the system results:
The rules of the fuzzy system will be stable as long as they do not contradict the knowledge and opinion of the experts and have the similarity of rule premise (SRP) and a different of rule consequent (SRC).
Jin have defined the following relationship for the stability of the fuzzy system:
R_i: If x_1 is equal to $A_{i1}(x_1)$ and x_2 is equal to $A_{i2}(x_2)$ and x_n is equal to $A_{in}(x_n)$ then y is equal to $B_i(y)$.

R_k: If x_1 is equal to $A_{k1}(x_1)$ and x_2 is equal to $A_{k2}(x_2)$ and x_n is equal to $A_{kn}(x_n)$ then y is equal to $B_k(y)$.

$$SRP(i,k) = \min_{j=1,\dots,n} S(A_{ij}, A_{kj}) \qquad (4)$$
$$SRC(i,k) = S\,(B_i, B_k)$$

$$Cons(R_i, R_k) = exp\left\{-\frac{\left(\frac{SRP(i,k)}{SRC(i,k)}-1\right)^2}{\left(\frac{1}{SRP(i,k)}\right)^2}\right\} \qquad (5)$$

By applying the relation in the set of rules of the designed fuzzy system, rules with a level of stability less than 0.2 were removed from the set of rules and stable rules are used as described in the table 4 in determining the learning style of learners.

Garcia [29] used a Bayesian Network to identify the learners' learning styles. Garcia has been described by a Bayesian Network to identify learners' learning styles. Selected variables include Felder-Silverman learning style model dimensions and determinant factors of these dimensions that were extracted from the learners' interaction in the network. The network was trained with data from 50 learners, basic probabilities, and expert knowledge. Then the trained network was evaluated with the data from 27 other learners. The network was able to identify learning style in an e-learning network with an average accuracy of 66%. Crockett [33-34] used a Decision Tree to model the learning style of 75 learners with 86% accuracy. Bernard [34], using Artificial Neural Network (ANN), identified the learning style of 127 learners with 80.7% accuracy. A comparison of these results is shows in Table 9.

TABLE IX. COMPARING THE ACCURACY OF THE PROPOSED METHOD WITH OTHER METHODS

Accuracy	**Method**
66%	Bayesian Network
86%	Decision Tree
80.70%	Neural Network
78.97%	Hidden Markov model
78.1%	PSO
78.1%	Ant colony system
78.4%	Genetic algorithm
89.07%	Fuzzy sets theory

VI. CONCLUSION

Today, there are different learners in the e-learning environment, and using from a learning path for a variety of learners reduces learning efficiency. So instead of a one-on-many instruction, having each learner learn according to the characteristics that affect learning will be very effective in the e-learning environment. In this study, despite the wide variety of indicators, learning style indicator was used to adaptive learning. Among the many learning style models, Kolb's learning style model was chosen. The reason of choosing the Kolb's style model in the proposed method is that in this theory, experience learning is a dynamic perspective of learning based on four- stages cycle in learning which simulates brain function and Since, in this research network behaviors that are performed dynamically in the network by learners are based, Kolb's learning style model is considered more appropriate choice. It should be noted there are several other indicators for learning adaptation, but according the proposed method of this research that is based on network behaviors the dimensions of the Kolb's model provide the adaptation fit.

Identifying the learning style of learners is done using the Kolb questionnaire. But this questionnaire will not be able to determine the learning style of learners with certainty because the problems:

One is the disruption of the training process (because the person has to answer it during the training process), and the second is the uncertainty of the answers (because the person may provide unrealistic answers to the questions). In this questionnaire, some learners are at the boundary between the types of styles and whose definitive learning style is not specified. This is due to the uncertain nature of learners' learning styles.

In this study, the fuzzy set theory method was used to identify the learning style of individuals. The fuzzy set theory provides a conceptual framework for systematically examining ambiguity and uncertainty, both quantitatively and qualitatively, and can well model the uncertainty in identifying a learning style. The designed fuzzy system uses learners' network behaviors to determine the style. The learners' network data were collected from the e-learning system and transformed into the corresponding network behaviors. The results of the fuzzy system are very close to the results of the questionnaire and this indicates that it can replace the questionnaire and to some extent eliminate the major problems in using the questionnaire and increase the learning efficiency.

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