# Learning Style Recognition: A Three Layers Fuzzy Cognitive Map Schema

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*Abstract*— **In Adaptive Educational Hypermedia Systems, among other parameters, the user's Learning Style plays a crucial role in effective on-line asynchronous learning. Cognitive psychology provides tools, such as questionnaires, that can monitor user's learning style. In this paper we introduce an adjustable tool for Learning Style recognition. It is built upon a well known and generally accepted Learning Style Inventory and applies a three Layer Fuzzy Cognitive Map Schema, which allows experts of cognitive psychology or experienced educators to tune up the system's parameters to adjust the accuracy of the learning style recognition.**

## I. Introduction

Nowadays, adaptive learning has been the critical asset in asynchronous learning systems aiming to provide the most promising outlook for diversifying learning [1]. In Adaptive Educational Hypermedia Systems (AEHS) among other components, the Learning Style (LS) plays a crucial role in adaptive e-learning [2], [3]. Researchers as Reye [4] face the question of establishing suitable techniques for handling the abstraction and uncertainty of the classification proposed by the cognitive theorists. In previous work [5], [6], two models for LS recognition have been suggested. Both are based on the Learning Style Inventory (LSI) introduced by Kolb [7]. In the first paper, a direct application of Kolb's inventory (via a probabilistic expert system) to the purpose of online LS detection has been suggested. In the second work, a "Learning Activity Factors" (LAFs) set has been used, to the purpose of LS detection as well. The list of LAFs and their relational links to the LSs are those indicated in Kolb's [16].

In literature on finds a wide variety of LAFs that have been introduced by cognitive scientists [14], [15]. LAFs serve as a medium to categorize the learner's cognitive preferences. It has been shown (Kolb [16]) that LAFs map on LSs. It also appears that degree of relation varies in terms of the LAF's influence on a certain LS. Such relations may be influenced by factors such as cultural environment, learner's age or psychological status influence. Experts as cognitive scientists or well experienced educators may recognize the degree of dependency on such factors and so they will be able to tune up an intelligent system in order to express in a best possible way a LS recognition procedure.

The term "learning style" is widely used in education and training and refers to a range of constructs from instructional preferences to cognitive style [9]. A wide range of LS inventories and related questionnaires have been proposed to be serving as LS recognition tools. In spite of this theoretical advance, individual researchers continue to design and develop their own instruments without sufficient regard for extant theory and measures, consequently there is the potential for real confusion amongst researchers and practitioners alike. As Furnham notices [10] "the proliferation of eponymous questionnaires that overlap considerably cannot be good for the development of the discipline". If the field is to progress there is a need to delineate cognitive styles and learning styles as separate constructs (if indeed they are such). The LSI has been the subject of analyses by Willcoxson and Prosser [11], Yahya [12] and Loo [13]. Their findings gave some support to the LSI's two-dimensional structure; however they did not consider LS in relation to other constructs. Kolb's learning theory sets out four distinct LSs (or preferences), which are based on a four-stage learning cycle, which might also be interpreted as a "learning cycle". In this respect Kolb's model is particularly elegant, since it offers both a way to understand individual people's different LSs, and also an explanation of a cycle of experiential learning that applies to the vast majority of humans.

In this work we introduce an adjustable tool that allows experts to reinforce the system's LS recognition ability. To this end, we develop a three layer Fuzzy Cognitive Map (FCM). The inner layer contains LSs, the middle one contains LAFs and the outer layer refers to the 48 statements one can find in the Kolb's LSI [7]. Each pair of layers (outer–middle, and middle–inner) consist a complete bipartite oriented and weighted graph. Student's responses to inventory reflect on certain LAFs according to relations which have been pointed out by experts. At a second step LAF reflect on LSs. Unlike the technique of LSs recognition which is based directly to student's response to LS inventory, the proposed schema allows the cognitive scientists or experienced educators to interfere, tuning up the system, in order to contribute on the accuracy of the recognition. For example, a teacher, having its own clear diagnosis on a learner's LAFs, can tune up the system's weights in order to adjust it in situation at hand.

Furthermore, techniques similar the one introduced in [8], reduces disturbances from misleading answers caused by several reasons. The system described in this work analyzes information from responses to questionnaire supplied by the

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system's descendant users (users that completed the questionnaire before the present user) and the system's present user as well. The proposed corresponding algorithm utilizes what appears to be reasoning capabilities so as to reach final LS estimations. Finally, the tool monitors the influence of lucky and slippery answers on LS estimation. This is achieved by introducing the Fault Implication Avoidance Algorithm (FIAA).

The rest of the paper is structured as follows. Section II describes briefly the principals of FCM. In Section III the logic and the implementation of FIAA are presented, following by Section IV which describes the proposed LS recognition procedure. Finally, the conclusions and the plans for our future work are given in Section V.

## II. FUZZY COGNITIVE MAPS

Fuzzy Cognitive Maps (FCM) is a soft computing tool which can be considered as a combination of fuzzy logic and neural networks techniques. FCM representation is as simple as an oriented and weighted compact graph. For example, the simple FCM, which is depicted in figure 1, consists of seven nodes which represent an equivalent number of concepts. Concepts represent key factors and characteristics of the modeled system and stand for inputs, outputs, variables, states, events, actions goals and trends of the system. Each concept $C_i$ is characterized by a numeric value $V(C_i)$ which indicates the quantitative measure of the concept's presence in the model. Each two distinct nodes are joined by at most one weighted arc. The arcs represent the causal relationships that relate pairs of connected concepts. The degree of causality of concept $C_i$ to concept $C_j$ is expressed by the value of the corresponding weight $w_{ij}$. Experts describe this degree using linguistic variables for every weight, so this weight $w_{ij}$ for any interconnection can range from –1 to 1.

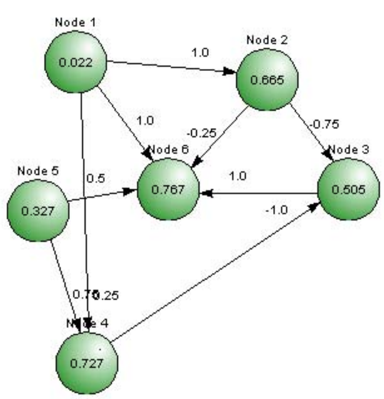


Fig. 1. An example of a Fuzzy Cognitive Map.

There are three types of causal relationships expressing the type of influence among the concepts, as they represented by the weights $w_{ij}$. Weights can be positive, negative or can also be zero. Positive weight means the increasing influence a concept implies to its adjacent concept of the graph, as on the other hand, negative weight means that as concept $C_i$ increases, concept $C_j$ decreases on the $w_{ij}$ ratio. In absence of relation between $C_i$ and $C_j$, the weight $w_{ij}$ equals zero.

Since there is a vast and sometimes controversial variety of expert's opinion on the weight with which a concept influences another concept, it is worthfull to introduce a suitable algorithm for the adjustment of the set of weights in FCM. As it has been already mentioned, the numerical values of weights have to lay in the interval [-1,1], as the FCM will converge either to a fixed point, or limit cycle or a strange attractor Dickerson and Kosko [17]. In the case in hands, where the FCM is called to support decision making process, as the recognition of learner's style is, it is better to converge to a certain region which is suitable for the selection of a single decision.

Initially, every concept gets a hypothetic value and as the time proceeds (i.e. new learners use the system), the values of the concepts change, as they are under the influence of the adjacent concepts and their corresponding weights.

At the step n the value $V^n(C_i)$ of the concept $C_i$ is determined by the relation

$$V^{n+1}(C_i) = f\left(\sum_{\substack{j=1 \\ i\neq j}}^{k} w_{ji} V^n(C_j)\right)$$

where $V^{n+1}(C_i)$ is the value of the concept $C_i$ at the discrete time step n+1.

For this research we used the more general formulation which is proposed in [5]

$$V^{n+1}(C_i) = f\left(k_1 \sum w_{ji} V^n(C_j) + k_2 V^n(C_i)\right)$$

Where $0 \le k_1 \le 1$ and $0 \le k_2 \le 1$.

The coefficient $k_1$ defines the concept's dependence of on its interconnected concepts, while the coefficient $k_2$ represent the proportion of contribution of the previous value of the concept in the computation of the new value. In other words, $k_2$ is the effect of the knowledge the system has gained by the previous users. We selected $k_1=k_2=0.5$ as this results in smoother variation of the values of the concepts after each recalculation and more discrete final values.

Function f is a predefined threshold function. Generally two kinds are used in the FCM framework. $f(x)=\tanh(x)$ is used for the transformation of the content of the function in the interval [-1,1]. We used the unipolar sigmoid function, as we want to restrict values of concepts between 0 and 1. The function is given by:

$$f(x) = \frac{1}{1+e^{-\lambda x}}$$

where $\lambda > 0$ determines the steepness of the sigmoid. Plots of the threshold function for various values of the constant $\lambda$ are shown in the figure 2. As $V(C_i)>0$ , these values easily become greater than 1 after some iterations. Taking a look at plot (b) in figure 2, we can easily understand that values greater than 1 are squashed towards value 1. This leads to discreteness loss that is needed in order to have a safe decision of user's LS. Increasing functions steepness makes things worse (plot (a) in figure 2). Selecting $\lambda=1$ we tried out translating function's graph to the right, which, as we will see later, gave greater discreteness to the values of output concepts.

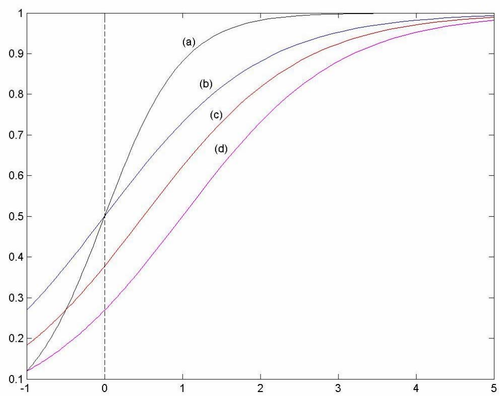


Fig. 2. Graphical representation of unipolar sigmoid function.
Plots for the cases: (a)→ f(2x), (b)→ f(x), (c)→ f(x-0.5), (d)→ f(x-1)

## III. Fault Implication Avoidance Algorithm

Let us consider three pairs to be selected from a questionnaire consisting of the statements (A), (B), and (C). Logical implication determines that once the statement (A) is chosen between (A) and (B) in the first selection pair, and (B) is chosen between (B) and (C) in the second selection pair, the choice of (A) instead of (C) is obligatory (Table I). As the first two selections lead to (A)>(B)>(C) order of preference. Alternatively, reverse choices in pairs 1 and 2 ((B) and (C) instead of (A) and (B) accordingly) leads to the order (C)>(B)>(A). In every other combination of choices in pairs 1 and 2, no logical implication appears and pair 3 remains open to choose from its statements. At this point a question arises: What if a selection in pair 3 can better represent the user's preference than pair 1 or 2, the system do not allow a choice to be made in pair 3 and moreover those choices lead to wrong order of (A) and (C). The answer is that pair 3 can only be "locked", ranking statements (A) and (C) in a wrong way, in the very rare case the user's choices in pairs 1 and 2 are both against his/her preferences. In case were only one choice from pairs 1 or 2 is against the user's real preferences, pair 3 remains "unlocked" waiting the user's selection. Obviously, the probability of two sequential "wrong" choices is considerably smaller than making one "wrong" choice, even in cases of statistical dependence.

TABLE I
Example of Fault Implication Avoidance

| Pair | Statement | Input Method |
|---|---|---|
| 1 | **A** | user selection |
| | B | user selection |
| 2 | **B** | user selection |
| | C | user selection |
| 3 | **A** | automatic selection |
| | C | automatic selection |

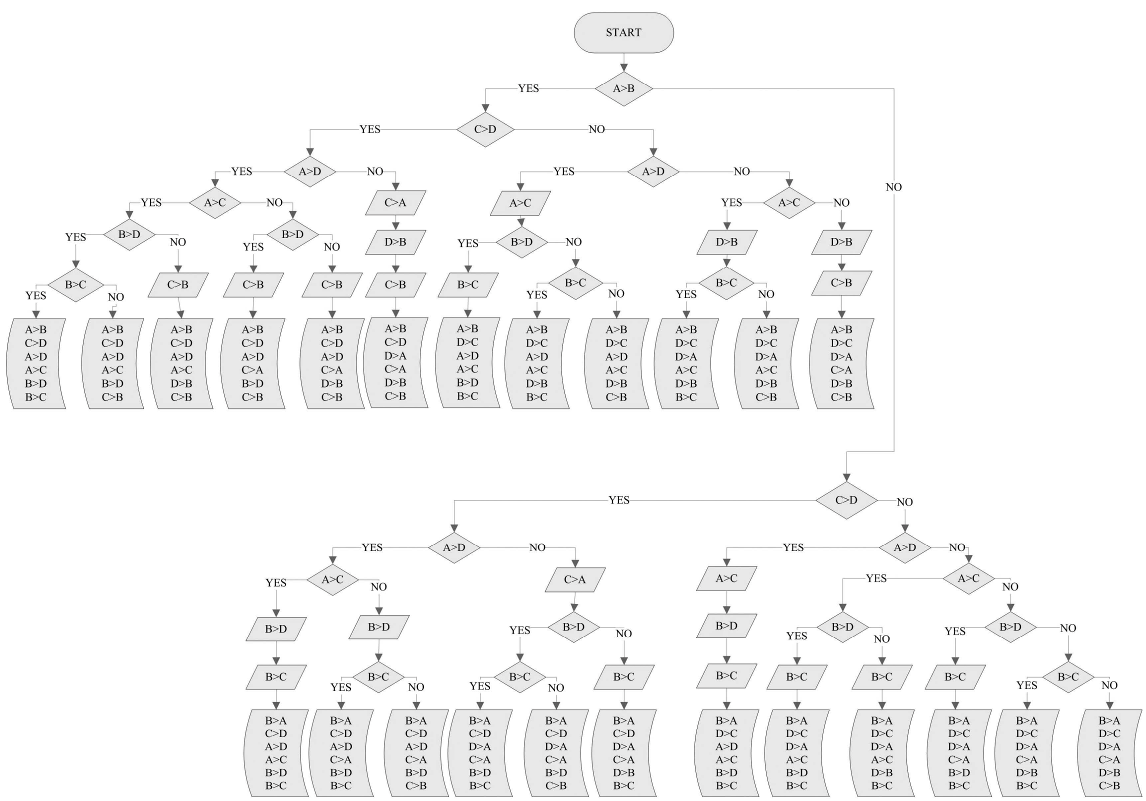


Fig. 3. Logical diagram of Fault Implication Avoidance Algorithm

Analogously, for more than three selections, the final ranking can be reached by responding to a subset of the set of selections pairs. Figure 3 presents a binary tree which is the logical diagram for a set of 4 statements as appears in each item of LSI. The paths end in every possible combination of responses a user can give in an item. Nodes of the tree represent the “logical ifs” i.e. the user’s choices in every pair of statements.

For example the leave [A>B>C>D] denotes the end of a sequence of choices at nodes (“logical ifs”) which are presented in Table II.

TABLE II
SEQUENCE OF CHOICES FOR LEAVE [A>B>C>D]

| |
|---|
| A instead of B |
| C instead of D |
| A instead of D |
| A instead of C |
| B instead of D |
| B instead of C |

TABLE III
SEQUENCE OF CHOICES FOR LEAVE [C>D>A>B]

| |
|---|
| A instead of B |
| C instead of D |
| D instead of A |
| C instead of A (disabled) |
| D instead of B (disabled) |
| C instead of B (disabled) |

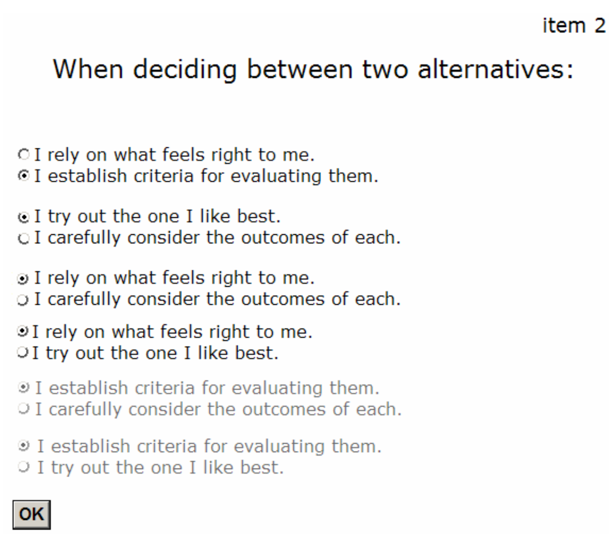

Fig. 4. Item example of revised on-line inventory. Pairs five and six are locked and automatically completed due to implication limitations. (no radio buttons are marked by default, the user must make the selection)

Apart from “logical ifs”, the parallelograms represent the statements that are “locked” because of FIAA. The “locked” statements are disabled or hidden (they are faded in the form), making them unable to be selected (figure 4). For example the leave [C>D>A>B] denotes the end of a sequence of unabled and disabled choices as appears in Table III.

In the printed LSI there are no such possibilities, as the student has to deal with every single selection pair in the item. It has been noticed that some students who succeeded an early final ranking, they conflict it by their late responses. The original printed LSI reduces fault logical implication influence on the final estimation by repeating the ranking procedure 8 times (8 items). Taking advantage of the computer capabilities the proposed FIAA makes a step further to face possible fault logical implications.

In our work, the application of FIAA in LSI provided the revised form of the inventory. In every inventory’s item, users respond to limited number of pairs which varies from three to six (figure 4). Therefore, a total number of 24 minimum up to 48 maximum selections are required. The remaining pairs take the right values automatically.

## IV. LEARNING STYLE RECOGNITION

Kolb’s learning theory sets out four distinct learning styles (or preferences), which are based on a four-stage learning cycle (figure 5), which might also be interpreted as a “learning cycle”. According to David Kolb (1999), diagnosis of LS can be based on the learner’s response to the inventory proposed by him. Based on a description of the way one learns as well as the way one deals with ideas and day-to-day situations in his/her life, this inventory has proven to be a useful diagnostic tool. The learner responds to an 8-item inventory. Each item refers to a certain issue which reflects on four different statements that match to user’s LSs. These statements, combined by two, produce a set of six selection pairs for each item, as presented in Section III. According to user’s selections, a final score is resulted and represented on a two-dimensional Cartesian plane giving a dominated vector located on a quadrant. In some cases the resulting vector lays on, or in the vicinity of the bisectors.

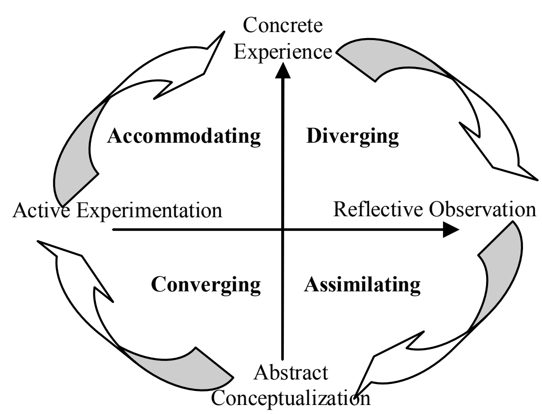

Fig. 5. Kolb’s Learning Cycle

Referring to Kolb’s LS inventory we introduce a table of possible qualitative relations of LS inventory’s item responses to LAFs (Table IV). Let us consider a set of LAFs, i.e. (I) Experimentation, (II) Influencing People, (III) Implementing a solution, (IV) Emotion/Intuition and (V) Scientific, Analytic, Theoretic. Let us now consider one out of the eight items in Kolb’s LSI, namely item 2. Using the FIAA a learner’s responds to item 2 result to the item’s statements final rank [A>B>C>D], so as the FCM’s upper layer takes values 1.00, 0.75, 0.50, 0.25 accordingly.

TABLE IV
EXAMPLE OF FUZZY RELATIONS
(Statements of Item 2 to LAFs)

| Statement | LAF | Linguistic Variable |
|---|---|---|
| A | Experimentation | weak |
| | Influencing People | none |
| | Implementing Solution | none |
| | Emotion/Intuition | strong |
| | Scientific/Analytic | very weak |
| B | Experimentation | weak |
| | Influencing People | none |
| | Implementing Solution | none |
| | Emotion/Intuition | weak |
| | Scientific/Analytic | very strong |
| C | Experimentation | very strong |
| | Influencing People | none |
| | Implementing Solution | strong |
| | Emotion/Intuition | strong |
| | Scientific/Analytic | weak |
| D | Experimentation | weak |
| | Influencing People | none |
| | Implementing Solution | none |
| | Emotion/Intuition | none |
| | Scientific/Analytic | very weak |

The fuzzy values that have been assigned in Fuzzy Analyst [18] appear in tables IV and V. The constructed FCM is presented in figure 6 and the results with a final rank of LSs appear in figure 7. The case in hands shows that Learner's responses to LSI item 2 imply that the leading LS is Active Experimentation (A.E.). Results from each inventory's item contribute to the statistic which produces the final LS recognition.

TABLE V
EXAMLE OF FUZZY RELATIONS (LAFs TO LSs)

| LAF | LS | Linguistic Variable |
|---|---|---|
| Experimentation | Concrete Experience | strong |
| | Reflective Observation | weak |
| | Abstract Conceptualization | normal |
| | Active Experimentation | very strong |
| Influencing People | Concrete Experience | normal |
| | Reflective Observation | very weak |
| | Abstract Conceptualization | weak |
| | Active Experimentation | strong |
| Implementing Solution | Concrete Experience | normal |
| | Reflective Observation | very weak |
| | Abstract Conceptualization | normal |
| | Active Experimentation | very strong |
| Emotion-Intuition | Concrete Experience | very strong |
| | Reflective Observation | weak |
| | Abstract Conceptualization | very weak |
| | Active Experimentation | strong |
| Scientific-Analytic | Concrete Experience | very weak |
| | Reflective Observation | strong |
| | Abstract Conceptualization | very strong |
| | Active Experimentation | weak |

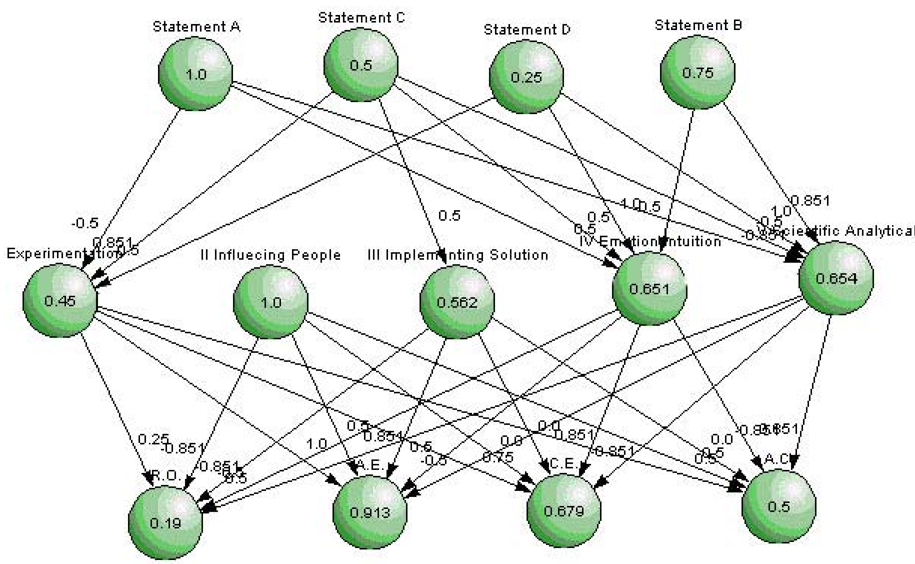


Fig. 6. The FCM for item 2.

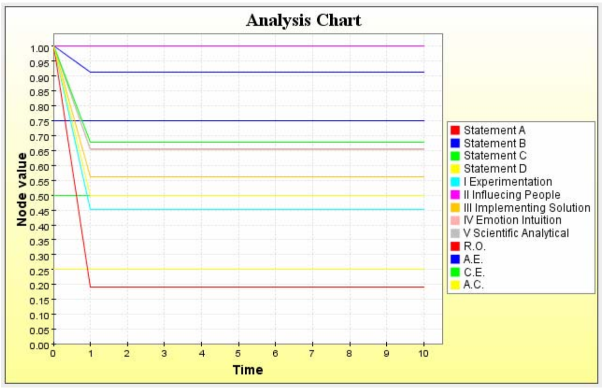


Fig. 7. Chart Analysis for item 2.

## V. Conclusion and Future Work

In this paper we described a tool for LS recognition. It has to be stressed out that the number and the type of the LAFs applied in the schema can be modified from experts in the field of cognitive psychology. Also, the fuzzy relations of each pair of layers (questionnaire statements-LAFs and LAFs-LSs) can be easily modified to refine the LS recognition efficiency. FCM is a tool that can provide a solid solution for LS recognition, as it can handle efficiently the fuzziness and uncertainty of a LS diagnosis.

Also the application of FIAA and the knowledge gained by the descendant users provide additional value to the proposed system.

An extended research is conducted with real learners answering the LSI and the gathered results will provide evidence on the accuracy and the efficiency of the FCM proposed in this work.

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