Intelligent System for Selecting Optimum Instructional Style(s) Based on Fuzzy Logic to Develop a Courseware (ISSIDC)

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***Abstract*- Instructor's teaching experience or instructional style (INST) is an essential factor in the knowledge transfer for T-learning [1], so in this paper I tried to cope (INST) in E-learning system as well. Specifically, this paper proposed (Methodological approach based on Fuzzy logic to Select the Optimum Instructional style(s) for Designing a Specific E-learning system" (MFSOI-DSE). The proposed (MFSOI-DSE) extends the fuzzy logic concepts and techniques in E-learning field, explicitly, in selecting an optimum (INST) for developing a specific courseware. In this paper I proposed a new procedure for representing the (INST) in quantitative values instead of qualitative description, using Frame of cognition/knowledge. In this paper, a conducted case study using the proposed procedure has met the selection of INST for developing a specific courseware with an expertise decision. Moreover, the paper specified the best software tools for building an automated system based on the above mentioned procedure in order to facilitate the (MFSOI-DSE).The topic of this paper lies on a multidisciplinary area of research, so it needs a solid background in computer science, Fuzzy logic and Instructional design field. Finally, I hope this paper will improve the quality of the E-learning systems based on IQP (Instructional Quality Profile) [1].**

Keywords*- *E-learning; Fuzzy logic; Courseware; Instructional style (INST); learning algorithm (L.A.), IQP.

I. INTRODUCTION

In reality, the selection of a required (INST) to develop a courseware contains uncertainty and imprecision of factors [2]; however, it needs special experience in the Education, precisely, in the instructional design field [3]. So this paper tries to use the Fuzzy logic concepts and techniques in order to find out an elucidation for this difficulty, mostly might be by automating the selection process.

(INST) vs. Learning algorithm (L.A.):

There are more than hundreds learning theories try to explain how the learning process occurs? [1] As well as how the knowledge transfer in the learning process?[4] i.e., inside the traditional classroom (T-classroom).

There are several possible (INST)s based on learning theories that aim to transfer the knowledge inside the T-classroom [5].

So, in computer science terms we can state that, "we have more than hundred possible learning algorithms (L.A.)s to transfer knowledge in E-learning system" [6].

In this paper I tried to find out a " ***Methodological approach based on Fuzzy logic to Select the Optimum Instructional style(s) for Designing a Specific E-learning system*" (MFSOI-DSE) . The (MFSOI-DSE) assists in automating the selection process of INS for (DSE).

II. METHODOLOGY

In this paper I used the fuzzy logic concepts, methods, and techniques to find out a new (MFSOI-DSE), so, I represent (L.A.)'s elements as linguistic variables, consequently, I used five linguistics labels to describe each (L.A.)'s elements, specifically, "Kernel, V-important, Important, Normal, and Not-important", furthermore, the Fig. 2, shows the using of the membership degrees and the frame of cognition.

There are many methods to evaluate the membership function $T(\chi)$ of an element [7]; in this paper I used the (HM) "Horizontal method" [8]. In (HM) method the Experts or references determine the membership function $T(\chi)$ for each (L.A.)'s elements [9]:

III. LITERATURE REVIEW

Formally, fuzzy logic can be defined as (Fuzzy logic is only a mathematical tool. It is possibly the best tool for treating uncertain, vague, or subjective information) [10].

Actually, this multidisciplinary area of research is still hot, and as far as I knew, there are very poor references cover this topic in details [11].

A. Procedure (MFSOI-DSE)

Steps of procedure (MFSOI-DSE):

- Procedure (MFSOI-DSE) : (Start)

Step-1 Calculate the "Importance value" of the (L.A.) elements as follow:

1.1 Assign the "important value" for each (L.A.) elements based on an Expert's knowledge or reference, and then use the "Compatibility measures" as follow: [see Figure 2]

The "Importance value" of (L.A.)'s element $T(\chi)$*evaluated* as follow:

A- 0 if ($T(\chi)$ Not belong to (L.A.)).

B- $(\chi - a)/(b-a)$ if $\chi \in (a,b)$

(The element outside the kernel: closer or far)

C- 1 if $\chi \in [a,b]$

(The element strongly belong to (L.A.), means inside the Kernel)

D - $(d-\chi)/(d-c)$ if $\chi \in (c,d)$

(The element outside the kernel: closer or far)

Hence,

Element-Importance value → (Compatibility measures + Experts knowledge).

Where "→": means "represented or Evaluated" by.

1.2 Refer to Experts or references in order to find out the "importance value" or the membership function of the (L.A.) element, and then calculate the Experts' or references' *average answers* based on (HM) method as follow:

A(x) = (Affirmative answer)/N

1.3 Evaluate the membership degree for each (L.A.) elements, using the following compatibility measures: (Assign a *fuzzy value for each* (L.A.) *elements*)

$$Comp(\mathrm{B},\mathrm{A})(u) = \sup_{u=\mathrm{A}(\chi)}\{\mathrm{B}(\chi)\}, u \in [0,1].$$

Or use the following formula,

$$Comp(\mathrm{B},\mathrm{A})(100\%) = \mu_{\mathrm{A}}(\chi)$$

Step-2 Calculates the total weights of the (L.A.) elements' using the following formula "Eq. 1":

$$Card(\text{learning algorithm}) = \sum_{\chi \in X} \mu_{\mathrm{A}}(\chi) \quad (1)$$

Step-3 Calculate the total weights of the ***selected*** (L.A.) elements- i.e. selected by the user of the *(ISSIDC)-* using the following formula:

$$Card(\textit{selected}\,\text{learning algorithm}) = \sum_{\chi_s \in X_s} \mu_{\mathrm{A}}(\chi_s)$$

Step-4 Calculate the ratio between "Total weights - ***selected*** (L.A.) elements'" and "Total weights *of* (L.A.) elements' ", using the following formula "Eq. 2":

$$\mathrm{RSWLA} = \frac{\sum_{\chi_s \in X_s} \mu_{\mathrm{A}}(\chi_s)}{\sum_{\chi \in X} \mu_{\mathrm{A}}(\chi)} \quad (2)$$

Step-5 Take a decision for selecting optimum (L.A.)- (The result)- based on the following criteria:

5.1 The (L.A.) will be selected as optimum (L.A.) for developing a specific courseware if and only if:

RSWLA > 0.7

(7o% is an accepted percentage criteria that determined by an expert or a reference [12]).

5.2 Otherwise, Rejected.

Step-6 End of the procedure (MFSOI-DSE).

The rest of this paper illustrates the derivation of the procedure (MFSOI-DSE) based on the Fuzzy logic concepts and techniques. Moreover the paper also covers a case study, as the following:

B. Derivation of the procedure (MFSOI-DSE)

Linguistic label and (L.A.): [13]

The Linguistic label can be extended in a (L.A.) domain by defining linguistic labels to describe each element of the (L.A.) (by the element I mean an item belongs to the (INST) either a fact or action), the following examples are possible linguistic labels that can be describing a (L.A.) element:

A. Very important.
B. Important.
C. Normal.
D. Not important.

Linguistic variable and (L.A.): [14]

The definition of Linguistic variable can be extended in a learning algorithm domain by defining the *learning algorithms elements* as **Linguistic variables** (e.g. in our case study , Merril (L.A.) elements are; Generality- Definition (attributes, relationships), and Instance - Examples (attributes present, representations) can be represented as **Linguistic variables).**

So, apply the main characteristics of the **Linguistic variables** against the Merril (L.A.)'s element , you will obtain the following facts:

A. Name, " Each element has a name"

B. Underlying universe, "Each element is a member of the (L.A.) elements' group".

C. Set of Linguistic labels,[Each element may be define as V.important, Important, …etc .].

So, obviously, the learning algorithm elements satisfied all the characteristics of the Linguistic variables.

Frame of cognition/ knowledge and (L.A.):

Is a very important concept in the fuzzy logic, because it considers as reference for assigning values for linguistic labels, i.e. it is a tool to transfer linguistic labels from quantitative to qualitative values [14].

Let "**(L.A.)** elements" defined as Linguistic variables.

Given the following linguistics labels to describe each **(L.A.)** elements: "”Kernel”, V_Important ", “Important ", "Normal", and "Not-important".

Using the membership degree, and the frame of cognition we can describe graphically the relationship between linguistics variables and linguistics labels [see Fig. 2] with the title (Frame of knowledge for (L.A.) elements) [14].

So, notice that there are some elements belong to "*two different linguistic labels* (e.g. v_important, and important)" , ***this means that, those elements belong to (L.A.) with different degrees, i.e. more closer to v-important or more closer to important, hence they are given a relative ‘membership degree’ to the learning algorithm according to their distance (closer or far).***

C. Weights of the (L.A.)s

In this part of the paper I explain how to transform (L.A.) from qualitative to quantitative values.

1. Criteria for (L.A.) Elements Weights (CFEW)

To find out the (CFEW) the researcher has introduced the concept of “**importance value**" for the (L.A.)s elements. This is a critical concept for (CFEW), it enables the possibility of comparing between the (L.A.)s elements, as well as transforming them from *qualitative* to *quantitative* values.

The "**Importance value concept**" based on three fuzzy logic concepts, kernel definition (Maximum value), Height of the fuzzy set, and normalized, with addition to membership function **[15]**21.

Zadeh proposed a series of membership functions that could be classified into two main groups:

1. Linear: Those made up of straight lines.
2. Gaussian forms: those made up of curves. [16]

The researcher interested in the linear functions, because it represents the required membership degrees in the (L.A.)s domain. One of the important linear functions is Trapezoid function or Trapezoid fuzzy set [17].

Based on the definitions of “ kernel (Maximum value), Height of the fuzzy set, and normalized”, as well as the definition of the Trapezoid function $T(\chi)$ [10], the researcher has established the (CFEW) as “ represents of (importance value) of each (L.A.)s elements as a *membership function* $T(\chi)$ „ , so, the Figure (1) illustrates the idea of (L.A.) selection.

D. The procedure (MFSOI-DSE)

In this part of the paper I will illustrate the essential points of the **procedure** (MFSOI-DSE) as follows:

- (L.A.) Element's weight

Let us assume that **(L.A.)** is a normalized fuzzy set, so the strongest element belong to the **(L.A.)** (strongest element defined as an ***element which Satisfies more than 70% of the L.A. objectives [11])*** should be given a weight as kernel or weight value equal to 1. Consequently, the other elements should assign weights less than 1, if they closer to the kernel, their weights are closer to 1, otherwise their weights depend on the *distant* from the kernel [see Fig. 3].

{ ***Note that the satisfaction of more than 70% of the L.A. objectives is a fuzzy value, i.e. lies in the interval [0,1]- in traditional logic it lies in the interval {0,1}***}.

Hence, the "importance value" of the learning algorithms' elements, can be define over the following ranges or intervals [see Fig. 2]:

Importance value of (L.A.) element $T(\chi) =$

1- 0 if $((\chi \le a)$ *or* $(\chi \ge d)$ (Not belong to L.A.).

2- $(\chi - a)/(b - a)$ if $\chi \in (a,b)$

(Outside kernel: closer or far)

3- 1 if $\chi \in [a,b]$

(Strongly belong to algorithm, inside the Kernel)

4- $(d - \chi)/(d - c)$ if $\chi \in (c,d)$

(Outside kernel: closer or far)

Methods used to determine the membership function (Weights)

-Determination of the Weights

The weights of the (L.A.)s elements should be *defined accurately*, and *efficiently*. If they badly defined the system will not work well, so (L.A.)s weights must be carefully defined.

As illustrated above, (L.A.) element's weight defines within an interval of the membership functions $T(\chi)$,(CFEW).

The membership functions $T(\chi)$ or "Importance value" for the (L.A.)s elements can be evaluated in several ways, all methods have focused on the following two points [16]:

1. The manner in which the uncertainty is to be represented.
2. Who to measure the point (1) above (e.g. expert or reference).

-Determination of the membership function $T(\chi)$ for the (L.A.) elements:

There are many methods to determine the membership function $T(\chi)$ of an element; in this paper the researcher has selected the following method:

-Horizontal method (HM) :(Experts or references)

(HM) method based on the answers of group of N "experts" [expert can be a reference]

1. The question takes the following format: can x be considered compatible with the concept A?
2. Only "yes" and "no" answers are acceptable.

So, the required answer will be calculated as follow:

A(x) = (Affirmative answers)/N

-Calculation of the (L.A.)s weights: (*Membership degrees of the elements*)

Compatibility measure [16] is a critical **concept in determination of the (L.A.) elements' weights**.

A- Calculation of the (L.A.) element's weight using compatibility measurements.

In this paper I calculate the weights of the (L.A.) elements using the following function:

$$\text{Compa(B,A)}(u_0) = \mu_A(\chi)$$

[Fuzzy *value*-weight of the element] . [18].

Where,

B = Fuzzy value "Approx. Satisfies more than 70% of the objectives of the required (L.A.) " [19].

A= Fuzzy concept "i.e. learning algorithm's element ".

u_0 = the exact percentage of compatibility measure between set B and set A.

$\mu_A(\chi)$ = Fuzzy value (Fuzzy percentage) for compatibility measure between set B and set A to be equal by the exact percentage u_0 .

$\mu_A(\chi)$ Determined by an expert or reference, known as membership degree.

This concept is very important in determination of the weight for a (L.A.)'s element, In this paper I calculate the "weight" of the learning algorithm element as follow:

-Weight of the (L.A.) element:

Let,

Set B equal the fuzzy value:

"Approximately Satisfy more than 70% of the required (L.A.)'s objectives ".

Let,

Set A equal "Any element of a (L.A.)"

Let,

u_0 equal 100%

Then,

Substitute in the following equation,

$$Comp(\mathrm{B},\mathrm{A})(u) = \mu_A(\chi)$$

So, you will get the following:

$$Comp(\mathrm{B},\mathrm{A})(100\%) = \mu_A(\chi)$$

Hence, $\mu_A(\chi)$ is equal the "weight of a (L.A.) element" .

So, **in this case the value of " Compatibility Measures"** $\mu_A(\chi)$ *-which determined by the expert(s) or reference*(s)- **is defined as "*weight*" for the learning algorithm's element.**

Procedure (MFSOI-DSE)

Example(1): Calculate membership degree of the (L.A.) elements of the Merril (L.A.).

Problem:

Find out the membership **degree** of the **Merril (L.A.)'s** element " Elaborations - Helps, Prerequisites, Context ", in Merril (L.A.) domain? [20].

Solution

Let,

A = "Elaborations - Helps, Prerequisites, Context"

Given,

B = **Fuzzy value** " Approx. Satisfy at least 70% of the objectives of the **(L.A.)**". So,

Use the formula:

Compa(B,A)(100%) = [Result] (Fuzzy value, weight of the element)

Hence,

Compa(B,A)(100%) = 0.9 (Provided by an expert or a reference [3])

So,

Let,

χ_1 = "Elaborations - Helps, Prerequisites, Context".

$\mu_{A2}(\chi_1)$ = membership degree of element χ_1 .

A2 = Fuzzy set " Merril (L.A.)".

Therefore,

$$\mu_{A2}(\chi_1) = 0.9$$

Hence,

"Elaborations - Helps, Prerequisites, Context" weight is 0.9 associated to Merril (L.A.)

(Solution ***completed***)

Use the relativity rule of weights as follow

$$\forall \chi, y \in X, \forall y \in [0,1] .$$

$$\mu_A(\lambda.\chi + (1-\lambda).y) \geq \min(\mu_A(\chi), \mu_A(y)) \quad [21]$$

To compare, relatively, between membership degrees of Merril learning algorithm elements.

Case study: Weights of the (L.A.)s and Frame of knowledge: (Importance degree).

(Frame of cognition, or frame of knowledge used as reference points for fuzzy information processing) [22].

Frame of knowledge is set of labels, usually associated to normalized fuzzy sets (according to definition of kernel (Maximum value)).[see Fig. 3].

Hence, we have the following associated static weights values:

- Kernel = area with $\mu_A(\chi_i)$= (1.0)
- V. important = area with $\mu_A(\chi_i)$ =(0.9)
- Important = area with $\mu_A(\chi_i)$= (0.7)
- Normal = area with $\mu_A(\chi_i)$ =(0.5)
- Not important = area with $\mu_A(\chi_i)$ =(0.0)

Where,

χ_i = represent the learning algorithm Condition.

i = 1,2,…, n.

So, based on the "compatibility measure" , "frame of knowledge", and the *experts' knowledge or references* "the importance value" or weight of each Merril learning algorithm's linguistic variable would be determined".

Hence, using compatibility measures.)[23], Card(A)[24],and Horizontal method calculate the weights of the Merril learning algorithm's **linguistic variables** as follow: Table (2)

Refer to Table (3) includes the following terms:

$\mu_A(\chi_i)$: Values of compatibility measures.

Where, i = 1,2, …, n.

χ_i : Represents condition, where i = 1,2,…,n.

So, similarly, the following Table (3) contains the compatibility measures of the rest of the Merril learning algorithm's linguistic variables.

-Calculation of the Total weight of the (L.A.) elements **(TWLA)**

To calculate the ratio of the Total weight **of the selected** learning algorithm's elements' with the Total weight **of the** associated learning algorithm's elements' , or cardinality of the **selected** learning algorithm's weight divided by the cardinality of the **equivalent** learning algorithm's weight, i.e.

Card (S*elected learning Algorithm*)/Card(*Learning Algorithm*)

Hence, we use the following equation "Eq. 3":

$$\text{Learning Algorithm's weight (TWLA)} = \frac{\text{total of the selected conditions' membership degrees}}{\text{total of conditions' degrees}}$$

or :

$$\text{RTWLA} = \frac{\sum_{\chi_s \in X_s} \mu_A(\chi_s)}{\sum_{\chi \in X} \mu_A(\chi)} \qquad (3)$$

The following numerical example illustrates how the system calculates the (RTWLA) of the learning algorithm.

Example (2): Apply the procedure (MFSOI-DSE)

A system developer needs to design a courseware, if he wants to deliver a course material using the following learning algorithm's elements:

- Objectives.
- Advisor strategies.
- Elaborations – Helps, Prerequisites, Context.

Calculate **(**RTWLA**)** for Merril learning algorithm such that "Eq. 4":

$$\text{RTWLA} = \frac{\sum_{\chi_s \in X_s} \mu_A(\chi_s)}{\sum_{\chi \in X} \mu_A(\chi)} \qquad (4)$$

Solution

Let us use the rule "Eq. 5":

$$Card(\text{learning algorithm}) = \sum_{\chi \in X} \mu_A(\chi) \qquad (5)$$

Let χ_1 , χ_2, and χ_3 define as follow:

χ_1 = Objectives.

χ_2 = Advisor strategies.

χ_3 = Elaborations – Helps, Prerequisites, Context**.**

So, (refer to the table (3), Merril learning algorithm elements' weight.) and calculate the following:

Card (Merril learning algorithm) = 1+1+0.7 = 2.7

Then, Merril algorithm selected weight = 2.7/ total of elements' weights

= 2.7/ 12 = .225

So, we can deduce that "Eq. 6":

$$\text{RTWLA} = \frac{\sum_{\chi_s \in X_s} \mu_A(\chi_s)}{\sum_{\chi \in X} \mu_A(\chi)} = \frac{2.7}{12} = .225 \qquad (6)$$

Compare (RTWLA),

If (RSWLA) > 0.7 then the learning algorithm (Accepted)

Otherwise (Rejected).

.225 < 0.7 $\Rightarrow$ (Algorithm rejected).

(Solution *has been completed*)

Hence, if the ratio of the total weights of selected elements divided by Merril elements' total weights greater than 0.7, so the (L,A.) is accepted otherwise rejected, i.e. the (L.A.) is suitable to be used for designing a required courseware or an E-learning system.

IV. Conclusions and Future Trends

This paper presents a new procedure (MFSOI-DSE) based on the fuzzy logic to facilitate the selection of the suitable instructional style to develop a specific courseware, so we extend the Fuzzy logic concepts and techniques into E-learning applications. The highlighted the important of the instructional styles in designing of the E-learning system. Furthermore the paper simplified the implementation of the E-learning systems by automating the selection process of the INST (Proposed automated system *(ISSIDC)* based on a new procedure to facilitate the design of E-Learning systems).

In future perspectives we aim to develop a system using XML to represent the knowledge base of the instructional styles that based on the learning theories, as well as using the proposed procedure to facilitate the selection of the suitable instructional styles to develop specific E-learning system. This system can be used either by Courseware developer or in general by instructors to improve the quality of teaching skills.

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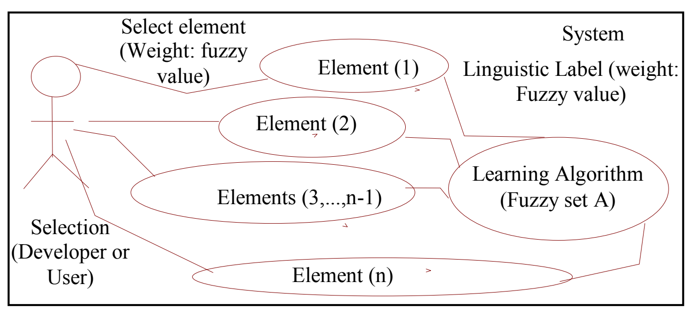
TABLE 1. MERRIL LEARNING ALGORITHM LINGUISTIC VARIABLE

i	**Elements (Linguistic variables) Conditions(χ_i)**	**X (Equal χ_i)**
1	Objectives Remember-Use).	1 χ_i Where, i = 1,2,3,..., n
2	Generality- Definition (attributes elationships).	
3	Instance - Examples (attributes present, representations)	
4	Generality Practice - State definition.	
5	Instance Practice - Classify (attributes present).	
6	Feedback - Correct generalities/instances.	
7	Elaborations - Helps, Prerequisites, Context.	
8	Advisor strategies.	

TABLE 2. TRAPEZOID FUNCTION FOR MERRIL LEARNING ALGORITHM'S LINGUISTIC VARIABLES (KERNEL).

i	**Elements Conditions(χ_i)**	**Fuzzy values Membership function T(χ), $\chi \in$ [a, b]**
1	Objectives (Remember- use).	1
2	Advisor strategies	1



Fi g. 1. Fuzzy representation of the (L.A.)s selection process.

TABLE 3. TRAPEZOID FUNCTION FOR MERRIL LEARNING ALGORITHM'S LINGUISTIC VARIABLES (OTHER ELEMENTS- "NOT KERNEL").

i	**Elements Conditions(χ_i)**	**Membership degree T(χ)** $\chi \in$ **(a, b) or (c, d)**
1	Generality- Definition (attributes relationships).	(χ -a)/(b-a) or (d- χ)/(d-c)
2	Instance - Examples (attributes present, representations).	
3	Generality Practice - State definition.	
4	Instance Practice - Classify (attributes present).	
5	Feedback - Correct generalities/instances.	
6	Elaborations - Helps, Prerequisites, Context.	

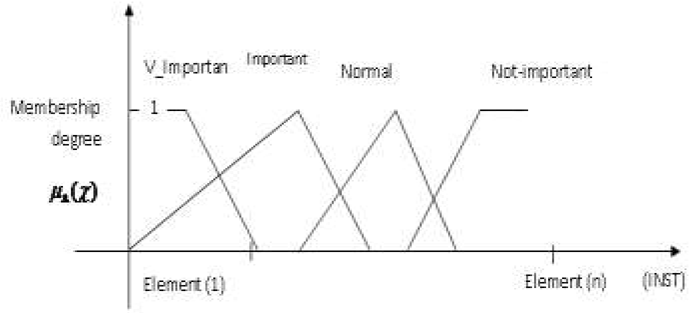


Fig. 2 Frame of knowledge for (INST) elements.

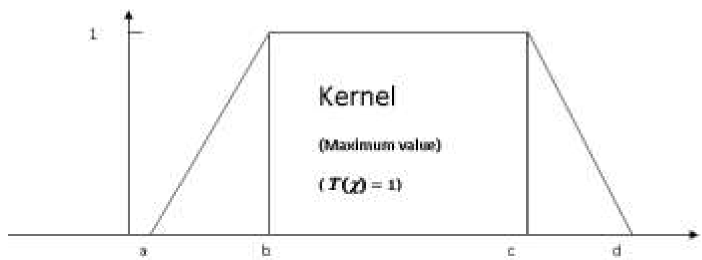


Fig. 3 Trapezoid function and definition of Kernel source [21]

TABLE 3. COMPATIBILITY MEASURES (WEIGHTS) FOR MERRIL'S LINGUISTICS LABELS.

i	**Conditions** (χ_i)	**Kernel** $\mu_A(\chi_i)$ = (**1.0)**	**V. important** $\mu_A(\chi_i)$ = **(0.9)**	**Important** $\mu_A(\chi_i)$ = **(0.7)**	**Normal** $\mu_A(\chi_i)$ **= (0.5)**	**Not important** $\mu_A(\chi_i)$ = **(0.0)**	**Expert-Reference**
1	Objectives (Remember-se).	X					[25]
2	Generality- Definition (attributes, relationships)		X				[25]
3	Instance - Examples (attributes present, presentations)				X		[25]
4	Generality Practice - State definition			X			[25]
5	Instance Practice - Classify (attributes present)				X		[25]
6	Feedback - Correct generalities/instances.			X			[25]
7	Elaborations - Helps, Prerequisites, Context.			X			[25]
8	Advisor strategies.	X					[25]
Total (weights) $\sum_{i=1}^{i=n} \mu_A(\chi_i)$		**2.0**	**0.9**	**2.1**	**1.0**	**6.0**	