The indicator of cognitive diversity in project-based learning

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Abstract: - The development of ICTs has emerged several electronic platforms, which contributed to a new mode of digital learning: E-learning. Moreover, new pedagogical approaches have been adopted, based on group learning, including project-based teaching. Project-based learning is an active learning method, based on group work to develop skills and build knowledge.
However, the group of learners is faced many challenges during the project, such as decision-making. the decisions by group , generate convergences and diversitys between the members, due to cognitive conflict.
Our approach in this paper is to treat the cognitive conflict in the group of students, by measuring the cognitive diversity indicator concerning the concepts of project, in decision making situations.

Key-Words: - Project-based learning, analytical hierarchy process, decision-making, cognitive map, Shannon entropy, cognitive diversity indicator.

1 Introduction

With technological development, new forms of group work have sprung up, particularly in the field of distance education (e-learning). E-Learning has experienced a lot of changes, and improved teaching conditions, while crossing the temporal and spatial constraints. Most learning platforms are specialised in content management, rather than processes related to distance learning. This problem is increasing in a social constructivist pedagogy that promotes group learning, decision-making group, and cognitive sharing.

The project-based teaching [1] [2] [3] [4] is marked by collaborative learning, social nature, which favours knowledge construction, the cognitive sharing, the criticism skills, and the group decision-making. Thus learners are confronted with situations of decision-making to make choices in order to solve a problem. The decision making in a pedagogical project [4] is a process which extends over all stages of the project: project selection, choice of materials, planning and assessment.

However, a decision making is effective only if the learners have well understood the problem, in order to choose a better solution among others. The assimilation of the given problem, and alternatives of choices is a function of the cognitive level of each learner. Thus, learners make the right decision, if they have a sufficient understanding of the project subject.

The tutor assesses the understanding of learners through measurement of cognitive diversity based on the weights of edges linking the concepts in the individual cognitive maps of learners.

In this paper, we propose a method for the computation of diversity cognitive of learners in the pedagogical project.

In the next section we will discuss the state of art of the pedagogical project. Then we will address the collective decision-making in a pedagogical project.

In the third section, we will apply the process AHP as a method for collaborative decision-making.

The fourth section is devoted to the introduction of cognitive maps, and its role in decision making.

We will propose in the fifth section, an indicator of cognitive diversity of learners to assess the level of cognitive diversity of learners during decision making.

A case study concerning a selection project of an urban site is an illustration of our indicator which is detailed in section six. The final section will highlight ongoing work and our main perspectives.

2 The project-based learning

The project-based learning consists in articulating learning around the learner, aroused by a realization of objectives, discovery and acquisition of knowledge through a project [5].

The project approach aims to transform the passive learners to autonomous learners, able to build knowledge through learning activities, which results in a production that reflects the goals and interests of learning.

Thus, the pre-existing conceptions of learners are linked to new information's, in order to build new knowledge, while promoting emotional engagement of the learner. The motivation factor plays an essential role to bring learners in more autonomy and initiatives.

By relying on the activity of the subject of study or production, we can put the project-based teaching in a learning problem and a social constructivist approach.

The Project-based teaching is characterized by a collective nature [7], which evokes a division of labour, and planning of tasks, by mutual agreement between project actors, resulting in an emotional investment and motivation.

In general, the project should lead to a production that characterizes the underlined objectives, when planning and design of the project. In addition, this production is a common task of collaborative work in the group, which consolidates the group cohesion, and increases the level of collaboration.

The collaborative work requires planning, and time management of the various stages of the project, and actions according to a schedule elaborated by project actors. During the various stages of the project, the group of students is brought to make decisions in a collaborative way, to solve the problem concerning the pedagogical project.

3 A decision making in a project-based learning

Within an educational project, the process of decision making [4] is a process fundamental in the learning scenario of stakeholders.

Decision making in a group, is performed by means of a consensus, vote, or a compromise.

In theory, the multi criteria decision making MCDM [8] is based on the aggregation of individual solutions in function of the weights of the evaluation criterions. Each learner solves individually the problem of the decision-making in the first step. In the second stage, the individual solutions are aggregated to obtain a collaborative solution.

In the case of project-based learning (Fig.1), learners are confronted with situations of problem solving, so they assign values to alternatives. The situations of problem solving are spread over all stages of the project.

So the students are assigned to activities to be performed by a prior planning. Then the tutor proposes a set of alternatives, and learners express their preferences for the solutions.

The AHP process [9] aggregates preferences of solutions, to provide a collaborative solution. The decision of the group is considered efficient if all these members reach consensus.

However, a consensus can be reached even if the group did not reach the same cognitive level, and shows cognitive differences. Hence, understanding the alternatives by the group members contributes to knowledge sharing, which generates an effective collective decision.

However the AHP process has a hierarchical structure of the evaluation criteria [9], which limits the non-hierarchical effects. In this respect, cognitive maps can play a major role in modelling the effects between the criteria in the form of cognitive maps. The cognitive maps elicit and represent the knowledge of learners [10], and share the knowledge of the group. The sharing of knowledge between members contributes to efficient decision-making.

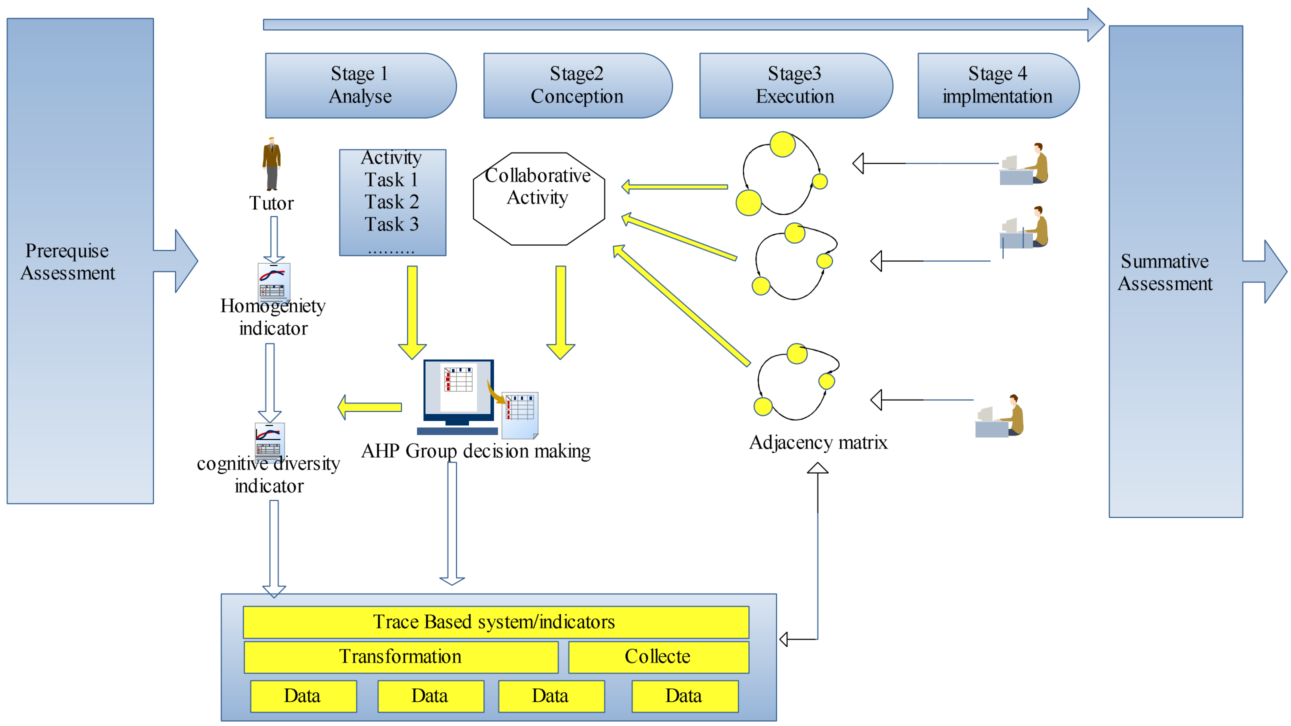

Fig1. Decision-making in a project-based learning

4 The cognitive maps of learners in a project-based learning

The cognitive maps elicit and represent knowledge of the group [10].A cognitive map is composed of two kinds of elements: concepts and relationships between concepts representing knowledge.

A cognitive map is formalized by a graph containing labelled nodes, and labelled edges linking them. As well, this inference mechanism in the cognitive map allows evaluating the influence relationships between two concepts of a map.

The cognitive maps containing causality edges are called the causal maps [11]. The causal relationships [12] are a special case of relationship influence. A relationship can be characterized by the following attributes: direction, polarity, power, probability, latency and certainty.

In a decisional context [13], this mechanism helps to evaluate different alternatives, to discover unforeseen effects and to design scenarios to solve the problem. The cognitive maps can be used as a tool for a decision making.

The process of decision making is composed of several stages: identify the problem, develop the decision criteria, yield the weights to criteria, develop the alternatives, analyze the alternatives, select the alternatives, implement the alternatives, and assess the results. So, a good knowledge of evaluation criteria involves an effective decision making.

Thereby, learners are brought to carefully study the problem, and represent knowledge in the form of individual cognitive maps [14], like in the decision-making context, the evaluation criteria constitute the concepts of cognitive maps (Fig .2).

The Individual representation of the evaluation criteria in a cognitive map, concerns the interaction effects between the criteria that will be used to obtain the final weights.

In our case, we use the fuzzy cognitive maps for deriving the influence between criteria, excluding loops in the concepts. The fuzzy cognitive maps [15] introduce the fuzzy measures to provide fuzzy relations among objects in complex systems. A propagation mechanism [16] allows simulating the interaction effects as a dynamic system.

In the initial state t_0, the concepts of the cognitive map have initial values, and these values evolve over time by propagation. At instant t_i, the concepts take new values based on the values at instant t_{i-1}. This operation is repeated until obtaining a stable state for the adjacency matrix.

We used threshold function, which indicates the relationship between the values of concepts, at instant t_i and t_{i+1}. The influence of one criterion on another criterion [10] is presented in the form of adjacent matrix according to the following formula:

$$C^{(t+1)} = S_{seuil}(C^{(t)}E) \quad (1)$$

with $C^{(t)} = (a_{ij}^{(t)})_{1\le i\le n, 1\le j\le n}$ the adjacency matrix at time t.

The threshold function $S_{seuil}(x) = x$ and the matrix E_{nxn} produce the influence matrix of the criteria. The vector $C(t_0)$ is assumed to be composed by values 1, so $C^{(0)} = I_{nxn}$ is an identity matrix.

This mechanism is applied until having a stable state of the adjacency matrix, for each learner (Fig.2).This steady matrix will be used for calculating the indicator of cognitive diversity at the instant t_n.

Firstly at the instant t_0, the tutor measure cognitive diversity indicator for the group of learners. Then, using the propagation mechanism, each adjacency matrix of learner reaches a steady state at a given time. Again, the tutor calculates the cognitive diversity indicator of learners in a stability state.

By comparing the measures, the tutor can detect evaluation criteria that require intervention in order to be well assimilated by learners.

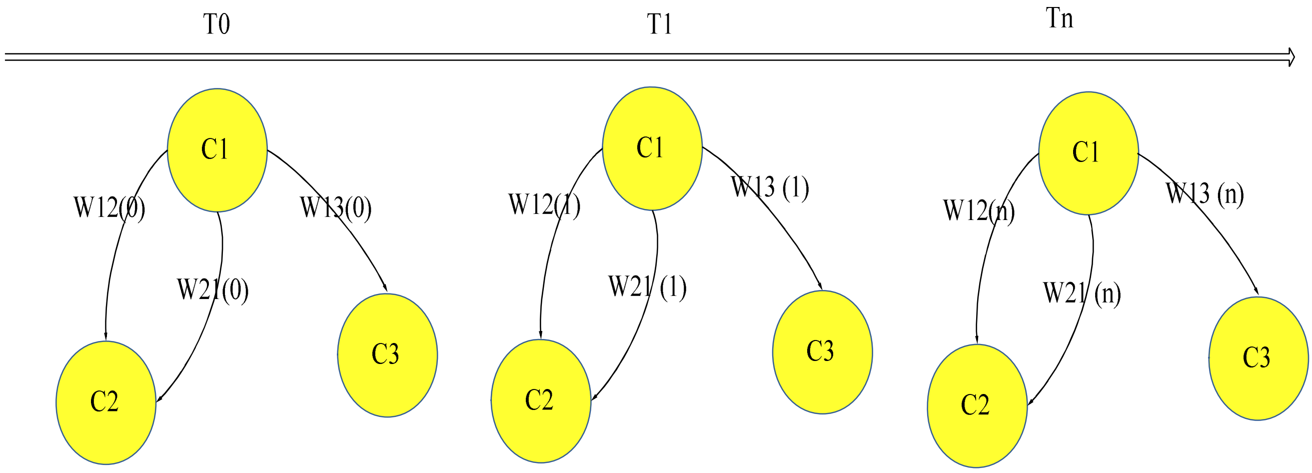

Fig. 2 The iteration of adjacency matrices

5 The measurement of cognitive diversity in a project-based learning

At each decision situation on a project, the students have to understand the problem before making a decision. The understanding of the study field depends on the cognitive level of each group member [23].

The indicators [18] play a major role in an educational project. The calculation of indicators allows having a view of the progress of the learner pedagogical scenario, by making a comparison between the values reached and the values fixed as a goal early in the project.

In our case, we chose to measure the cognitive differences of learners during a decision-making in an educational project [19] [20].

This indicator is based on the entropy of Shannon [21]: $H(X) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)$ (2)

The Shannon entropy [21] quantifies the distribution of the differences between values in a community. In the discipline of biology [22], the entropy of Shannon concerns the identity of species in a sample of a community of many species.

In a collective decision, learners must assign weights to the evaluation criteria, which constitute an input for the AHP method [9]. Our approach consists of asking learners to build individual cognitive maps. The cognitive map is composed of domain concepts which are the subject of the study. The tutor proposes a list of concepts (evaluation criteria) to learners, and asks them to draw edges of influence. The values of influence edges are selected on a Likert scale [23].

The Likert scale is a one-dimensional ordinal scale composed of ordinal values used to collect the data by means of categories. The type of data frequently collected involves determining the attitude or the feelings towards the attributes.

The Likert scale is expressed by sentences with categories of choice, classified from value 'total agreement' to 'total disagreement'. The choice of value Likert scale by the participant must belong to a single category. The Likert scale is presented by two to nine categories used to convert the opinions to values [25].

Moreover, in a group of k learners the Shannon entropy alpha is the average of individual entropies

$$H_\alpha = -\sum_{j=1}^{k} w_j \sum_{i=1}^{N} p_{ik} \ln(p_{ik}) \quad (3)$$

w_j: is the weight of the learner j in the workgroup. In this case, we assume that learners have the same weight.

p_{ik}: is the probability of the distribution of the distances.

The Distance [24] is measured between the a_{ij} values of the assigned weights by learners to the edge linking two concepts of the graph, and the average value of the weights given by learners to the edge using the following formula:

$$d = \left| \frac{a_{ij}^k - \overline{W_{ij}}}{n} \right| \quad (4)$$

a_{ij}^k : The value of the influence of the concept C_i to C_j in the cognitive map of the learner k.

$\overline{W_{ij}} = \sum_{k=1}^{n} W_{ij}^k$ The average values of the weights given by the learners to the edge (C_i, C_j), and n the number of learners.

The alpha diversity of the first order is given by:

$$D = \exp(H_\alpha) \quad (5)$$

So, the alpha diversity is a measure of cognitive diversity of learners around an edge (C_i, C_j).

The measurement of the degree of evenness gives cognitive deviation of the individual compared with the group cognition:

$$U^k = \frac{H^k}{\log_2(n)} \quad (6)$$

H^k : The Shannon entropy of the edge between two concepts of the cognitive map.

When H^k is close to 1, then the distribution is even. Otherwise the distribution D_{ij}^k is not uniform and H^k is close to 0.

6 Case study of a project : selection of an urban site

For example, we will use the values of the study looking at the choice of an urban site in a construction project [3]. The group consists of three students who expressed their preferences on five alternatives.

The evaluation criteria regarding the selection of sites are: the distance of habitats, the distance of hotels, distance from the main street and the distance from the highway.

The tutor assigns to learners the following activities: measuring distances between sites and habitats, measuring the average distance between sites and highways, measure the distance to the main avenue, estimate the cost of construction sites.

After have performed the tasks, each student attributes the preference value for each site according to the evaluation criteria. Using the AHP method [3], we find the solution of the group by aggregating the values of the priorities of each solution. The individual preferences and group are ranged for each alternative using Likert scale [23].

The indicator of homogeneity among members of learners group [10], allows us to detect disagreements between group members. Therefore, one must measure the cognitive differences on the edges in the individual fuzzy cognitive maps.

The individual fuzzy cognitive maps represent influences between evaluations criteria cited above. The influence values belong to the Likert scale.

We assume that the edges in the fuzzy maps are bidirectional, and have no loop effects.

We limit the site selection to following criteria [24]: C1: the distance of habitats, C2: the distance of hotels, C3: the distance of highway. The group of learners is composed by three learners: L1, L2, and L3.

The individual cognitive maps are presented in Fig.3, by graphs and relationships between concepts by adjacency matrix

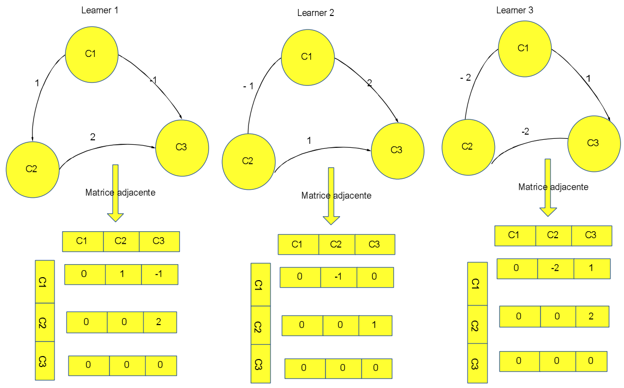

Fig.3 The adjacency matrix of the learners L1, L2, L3

After having developed the adjacency matrices of the three learners, the tutor measures the degree of cognitive diversity at t_0, for each edge of the graph.

First of all, we identify the edges in the matrices between the criteria (C_1, C_2), (C_2, C_3), and (C_1, C_3).

For example for the edge (C_1, C_2), the average weight for learners L1, L2, and L3 is measured by the formula: $\overline{W_{12}} = \frac{1}{3}[1+2-1] = \frac{2}{3}$.

Thus, the distance between the values of the weights assigned by the learners and the average weight is:

L1: $W_{12}^{1} = \left| \frac{1-\frac{2}{3}}{3} \right| = \frac{1}{9}$, L2: $W_{12}^{2} = \frac{\left| 0-\frac{2}{3} \right|}{3} = \frac{2}{9}$, and

L3 : $W_{12}^{3} = \frac{\left| 1-\frac{2}{3} \right|}{3} = \frac{1}{9}$.

The distance measured between the weights of edges in the individual fuzzy cognitive maps and the average value of the group is reported in Table 1.

Table 1: the distance matrix

	Learners		
Edge	L1	L2	L3
(C1,C2)	0,111	0,222	0,111
(C1,C3)	0,444	0,222	0,222
(C2,C3)	0,444	0,111	0,111

By dividing the values of the distance matrix (Table 1) by the sum of distances, we get the probability distribution of the distances (Table 2).

Table 2: The probability distribution of distances

	Learner		
Edge	L1	L2	L3
(C1,C2)	0,111	0,444	0,556
(C1,C3)	0,444	0,222	0,222
(C2,C3)	0,444	0,889	0,889

Using the equations (3) (4) (5) and (6), the index alpha, the alpha diversity, and uniformity are calculated for each edge between concepts (Table 3).

Table 3: the indices of edges between concepts

Edges	alpha index	alpha diversity	uniformity
(C1,C2)	0,9433	2,5686	0,8587
(C1,C3)	1,0397	2,8284	0,9464
(C2,C3)	1,0549	2,8717	0,9602

The (C_2, C_3) edge shows an index of alpha diversity superior to other edges (C_1, C_3), and (C_1, C_2), so the probability distribution is superior to others.

However the (C_1, C_2) edge index shows the lowest alpha diversity, therefore greater diversity on this edge is noticed. We conclude that the edge (C_1, C_2) presents a cognitive diversity, so a cognitive conflict occurs in the group at the initial time t_0

The tutor uses a propagation mechanism [16] to simulate the influence of the criteria in the cognitive maps of learners. After having simulated the influence using formula (1), the tutor checks its impact on cognitive diversity of group members.

For learner L1, we notice in Fig.4 that the matrix is steady at instant t_2, so at t_3 we have $C^{(3)} = C^{(0)}$.

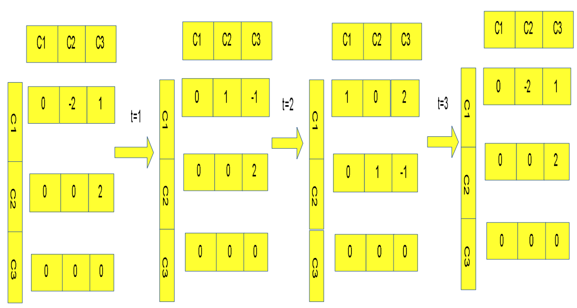

Fig.4 the propagation of the fuzzy cognitive maps for learner L1

Similarly, for all other learners in the group, the simulations of influences are carried out in cognitive maps, until a steady state of matrix is reached. We notice that all learners have reached a steady state at instant t_2 .

The tutor calculates the degree of cognitive diversity among learners, after propagation of influences (Table 4).

Table 4: the indices of edges after adjacency matrix iterations

Edge	alpha index	alpha diversity	uniformity
(C1,C2)	1,0397	2,8284	0,9464
(C1,C3)	1,0397	2,8284	0,9464
(C2,C3)	0,9433	2,5686	0,8587

The edges (C_1, C_2) and (C_1, C_3) show a diversity index alpha higher than the edge (C_2, C_3) , therefore the probability of distribution is superior to others.

While the edge (C_2, C_3) presents an alpha value greater at time t_0 . We conclude that the edge (C_2, C_3) presents a cognitive diversity therefore a cognitive conflict within the group at the time t_2 .

So, the edges $(C_1, C_2$ and (C_2, C_3) have to be checked, because they have a cognitive diversity while the edge (C_1, C_3) remains steady, and presents an homogeneity compared to other edges. The edges around the concepts C2 present diversity, consequently the concept C2 is not well understood by the students.

The tutor must check the degree of understanding of the concept C2 through questionnaires or quizzes. Indeed the tutor can assign new activities for learners to fill this issue, using materials and documentations.

After that, the tutor demands the learners to perform new fuzzy cognitive maps, and he verifies the cognitive diversity of the group again.

Next, this step is iterated until having a cognitive convergence, and then the tutor derives the overall weight vector of criteria, using the normalization of the local weight vector and the matrix steady as follows [4]:

$$W_{tot} = z + \left[C^{(t)} \times z\right] (7)$$

z : The local weight vector.

λ : The largest element of z .

C : The adjacency stable matrix.

γ : The maximum of the sums of the rows of a matrix $C^{(t)}$.

For example it is assumed that learner L1 yields the comparison matrix of criteria C1, C2, and C3 (Table 5):

Table 5: comparison matrix and vector local weight

Criteria	C1	C2	C3	Local Weight
C1	1	1/3	1/5	0,118
C2	3	1	2	0,501
C3	5	1/2	1	0,380

Using the steady adjacency matrix after propagation of influences and by applying formula (7), the final weight vector of the criteria is derived (Table 6):

Table 6 : Final weight vector

Criteria	Final Weights
C1	0,996
C2	0,622
C3	0,38

After obtaining the final weight vector, the process of AHP is used to obtain the ranks of alternatives for selection of urban sites. The classification of alternatives according to each learner is aggregated by the geometric mean [24], to obtain the final classification of alternatives according to the group. Indeed, the final ranking of alternatives in this case provides an appropriate choice of the urban site, while limiting the cognitive diversity of the group.

7 Conclusion

In this article we propose a cognitive diversity indicator of learners in a project-based learning. The computing of this indicator, aims to assess the understanding of learners during the learning scenario.

The control and monitoring of learners in stages of the project serve to regulate the path of learners. The Learners differ in their cognitive degree on domain concepts, which affects the homogeneity of the group and increases the cognitive diversity, which may doom the project to failure.

Consequently, the tutor drives the learners to new activities, in order to understand the concepts of the domain, and make appropriate decisions for the solutions of the problem.

However this work is limited to the calculation of cognitive diversity in the process of collaborative decision-making treated with AHP method, while cognitive diversity can arise in all learning situations during the project.

There exist other limitations of our method, such as excluding loop effects of edges in cognitive maps of learners, and use the values of the Likert scale.

In addition, learners are brought to draw cognitive maps, manually which proves difficult in the case of a large number of concepts and arcs.

In perspective of this work, we will cover the case of loops in the cognitive maps, and define a formula to calculate the indicator of cognitive diversity in all learning situations during a project. In addition, we will extend the scope of the types of preferences to values of fuzzy kind.

In the case of large cognitive maps, we can use metaheuristic algorithms, for the automatic construction of cognitive maps, to guide learners in developing maps.

Then we proceed to deploy our approach for calculating indicators in an electronic platform as a web service. We will automate the calculation of indicators by an algorithm, which will be integrated into a Web service to cross the constraints of interoperability between software of E-learning platforms.

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