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ICALM: an Intelligent Mechanism for the Creation of Dynamically Adaptive Learning Material

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Abstract: In this paper, an intelligent mechanism (ICALM) that allows an adaptive learning system to create and adapt dynamically the learning material on the fly, is presented. ICALM takes into consideration each time the needs and abilities of each individual learner and adapts the learning material that is addressed to the learner at three levels. These three levels are: 1) knowledge level, 2) content, 3) display mode. The presented intelligent mechanism uses artificial neural networks, a method of multi-criteria decision analysis and machine learning techniques. The presented mechanism has been incorporated in two adaptive e-learning systems and was fully evaluated through questionnaire and t-test. The evaluation results are very encouraging showing that ICALM provides great assistance to learners in a computer-aided instruction environment.

Keywords: Adaptivity, Adaptive learning material, Intelligent tutoring systems, Adaptive learning system, Learning style, Machine learning, Artificial neural network.

1. Introduction

Nowadays, in the digital era, there is a fertile ground for research in the area of e-learning and computer-aided instruction. Furthermore, the rapid development of the information and communications technology introduce novel approaches and tools in digital education. As such, technological advancements can serve for a student-centric learning experience since it provides tools and mechanisms which can model the students' learning goals, needs and preferences, cognitive levels, current degree of knowledge and specific requirements for effective e-assessment [1]. Moreover, the socio-economic changes worldwide necessitate the employment of new technological approaches in education; hence, they give birth to e-learning, which is a way of distance education that overcomes the obstacles posed by place and time, offering a more adaptable instruction in comparison to traditional classrooms [2]. However, e-learning systems are used from heterogeneous groups of learners meaning that such groups are distinguished by different needs, preferences and interests [3]. Also, novel approaches in digital education necessitate the refinement of the learning content objects, activities and interaction with the e-learning platform towards a personalized involvement in the tutoring process [4]. So, there is a growing need for tailored education. This is achieved by the incorporation of "intelligence" into the teaching and learning processes of e-learning systems, since it allows the provision of personalized instruction to students.

The employment of artificial intelligence (AI) techniques in learning systems can make them able to adapt the learning material or the tutoring and learning processes to each individual student's needs and abilities, offering him/her a personalized learning experience. More specifically, such techniques allow the perception and determination of learners' needs [5-6]. Also, they help the system create a routine for each learner concerning the dynamic adaptation of the learning and teaching processes, including the delivery of the domain being taught and the tailored assessment strategies, etc. [7]. As such, intelligent and adaptive educational systems usually provide an individualized learning path to each student.

An adaptive system must be capable of managing learning paths adapted to each user, monitoring user activities, interpreting those using specific models, inferring user needs and preferences and exploiting user and domain knowledge to dynamically facilitate the learning process [8]. That is the reason for the fact that adaptive educational systems and applications use a variety of AI techniques [9]. Examples of such techniques are the artificial neural networks (ANN) and the machine learning (ML) techniques.

Taking into consideration the above, this paper presents an intelligent mechanism that allows an adaptive learning system to create and adapt dynamically the learning material on the fly, taking into consideration each time the needs and abilities of each individual learner [10]. The presented mechanism is called Intelligent Creator of Adaptive Learning Material (ICALM). It uses a combination of AI techniques. Particularly, it uses artificial neural networks, a method of multi-criteria decision analysis and machine learning techniques. ICALM adapts the learning material that is addressed to a particular learner at three levels: 1) knowledge level, 2) content of the learning material (which concepts will be presented and focused), 3) display mode of the learning content (i.e. video, text, images, audio etc.). The knowledge level of the students is used to identify the domain knowledge concept. The artificial neural network takes as input the learning style of the students which is based on the VARK model (Visual, Auditory, Reading and Kinesthetic Learners) and gives as output the display mode of the learning material. The calculation of the activation function of the presented ANN is based on the Weighted Sum Model (WSM), which is a method for multi-criteria decision analysis. Regarding the partitioning of students' learning style, it is specified using the k-means clustering algorithm. Finally, the types of learners' errors, which are diagnosed using machine learning algorithms, and specifically String Matching algorithm and String Meaning Similarity technique, serve for the content of the domain concept.

As a testbed for our research, two fully operating and evaluated e-learning systems have been used: 1) a web-based educational application for programming languages tutoring and 2) a web-based e-learning system for English and French language tutoring. Examples of operation of these two systems, using ICALM, attests that ICALM is proved to be effective for optimizing e-learning, while providing great assistance to learners in a computer-aided instruction environment. Finally, a wide-range evaluation is presented. Evaluation was conducted using questionnaire and t-test. Its results are very encouraging, showing that the modules of ICALM incorporating either machine learning or an artificial neural network and the weighted sum model can enhance computer-aided instruction.

The remainder of this paper is organized as follows. In Section 2 related work about adaptive educational system, artificial neural networks, machine learning techniques and decision analysis is presented. Section 3 describes ICALM. Evaluation process and results are presented in Section 4. Finally, in Section 5, conclusions are drawn and future plans are discussed.

2. Related Work

2.1. Adaptive Educational Systems & Applications

Adaptive educational systems monitor important learner characteristics and make appropriate adjustments to the instructional milieu to support and enhance learning [11]. An adaptive educational system has to provide personalization to the specific needs, knowledge and background of each individual student. In literature review there are a large number of adaptive educational systems and applications that integrate a variety of intelligent techniques and approaches [9].

2.2. Artificial Neural Networks

An Artificial Neural Network (ANN) mimics certain aspects of the information processing and physical structure of the human brain with a web of neural connections. They are used in the field of e-leaning towards providing personalization to students' needs by finding the similarity of the domain concept data representation pattern between the students' and the learning object's profiles [12-13]. In [2] and [3], the authors focused on the adaptation of the e-learning system to the students' specific needs and preferences using ANNs. Other authors used ANN to form a recommendation system to support students [7] by delivering them adaptive instruction [5, 14], or proposing them a learning path that meets in a better way their needs and abilities [14]. Finally, ANN has been also used for emotion recognition in e-learning systems [6, 13].

2.3. Machine Learning Techniques

Machine Learning (ML) is related to algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on models and inference instead [15]. It involves algorithms that predict possible outcomes based on students' data. The system identifies certain patterns and trends, and then learns from the data in order to provide greater personalization. ML techniques have been employed towards offering individualized learning pathways. For example, in [15-17], the authors employed machine learning techniques in order to support collaborative learning and find patterns of interaction between learners showing that prior knowledge and communication skills of learners are likely to influence effectiveness of collaborative learning. Other efforts have been focused on the amelioration of learners' knowledge sources as well as on adaptive pedagogy. For example, in [18-20], machine learning techniques have been used in order to increase student engagement and improve learning outcomes. A lot of research effort has been also placed on the diagnosis of mistakes using machine learning. For example, in [21-23], the authors reported that e-learning can be enhanced by the identification of learners' errors and the adaptation of the teaching strategy to the weaknesses of students.

2.4. Decision Analysis

Furthermore, decision analysis is also employed in the field of e-learning. It is used to build systems, designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as if–then rules [16]. Decision analysis is mainly used in circumstances that a decision has to be taken. As an example, in e-learning, decision analysis is used to specify the proper domain knowledge to be delivered to students or the appropriate assessment to be given to students. Decision analysis processes have been used in the related scientific literature in order to provide tailored assessments to students [24-25]. For example, in [25], the authors create automated adaptive tests using multiple-criteria decision analysis taking into consideration multiple students' criteria along with the types of exercises and the desirable learning objective. Also, in [26] a decision-making model and method are proposed to evaluate suitability, acceptance and use of personalized learning units. Furthermore, present multi-criteria decision analysis approaches for selecting and evaluating digital learning objects [27].

3. The Description of ICALM

ICALM is the name of the presented Intelligent Creator of Adaptive Learning Material. It combines a variety of AI techniques. AI techniques. Particularly, it uses artificial neural networks, the Weighted Sum Model (WSM), which is the best known and simplest MCDA method for evaluating a number of alternatives in terms of a number of decision criteria [28], and machine learning techniques (String Matching algorithm, String Meaning Similarity technique and k-means clustering algorithm). ICALM's aim is to adapt the learning material that is addressed to a particular learner at three levels: 1) knowledge level, 2) content of the learning material (which concepts will be presented and focused), 3) display mode of the learning content (i.e. video, text, images, audio etc.). For the adaptation of the learning material to the knowledge level of the learner, the system checks the results of the learner's assessment and decides which the concepts are that coincide with her/ his knowledge level. The selection of the content of the domain concept is based on the types of errors that the learner usually does. The diagnosis of errors' types is achieved through the String Matching algorithm and String Meaning Similarity technique. In addition, the decision for the display mode of the learning material is based on the learning style of each particular learner and is achieved through an artificial neural network in conjunction with the weighted sum model. The logical architecture of ICALM is depicted in Fig. 1. The mechanism of adaptation of the learning material is described in more details below for each adaptation level.

- 1st level of adaptation: knowledge level: It concerns the domain concept or concepts that have to be delivered to a particular learner meeting her/his educational needs and abilities. The main criterion for this is the learner's knowledge level. The learner's knowledge level is determined by the results of her/his assessments. According to these results, the system selects the domain concepts of the learning material that coincides with the learner's knowledge level and delivers them to her/him for studying.

- 2nd level of adaptation: contents of the learning material: It concerns the issues of each delivered domain concept that have to be presented and focused for a particular learner. For deciding about that issues the types of errors (i.e. grammatical, syntactic, logical or knowledge transfer mistakes in language learning) that the learner, usually does, have to be detected. The diagnosis of errors' types is based on String Matching algorithm and String Meaning Similarity technique. String Matching algorithm tries to find strings that match a pattern approximately in order to identify the kind of mistakes between grammatical, syntactic or logical. String Meaning Similarity is responsible for identifying knowledge transfer mistakes in language learning and works by finding and translating patters, determining the source language of knowledge. Since it is not the scope of this paper to present how the aforementioned algorithms function, an in-depth analysis of them is presented in the authors' previous research works [29-30].

- 3rd level of adaptation: display mode of the learning material: It concerns the way of presentation and display of the learning material. For example, the content of a domain concept can be presented through a video or a text or using images or audio files, etc. The main criterion for choosing the best suited to a particular learner's needs display mode is her/his learning style. In our model, we use the VARK model

(Visual, Auditory, Reading and Kinesthetic Learners). The learning style of the learner, which is based on the VARK model, is input in an artificial neural network. More specifically, each sensory modality of the VARK model uses different weights. This means that if a leaner is a visual learner wants to be shown the learning content in the mode of text, video narration, images, diagrams and examples but in a different percentage. The other modalities take the weights following the same rationale. Then, the activation function, which is based on WSM, determines the output of neural network by mapping the resulting values, as shown in Fig. 2.

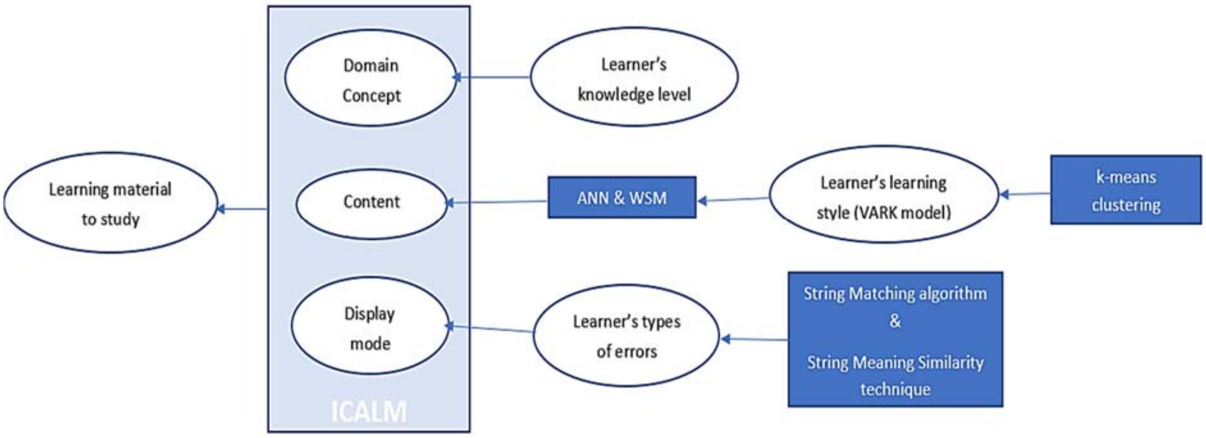

Fig. 1. The logical architecture of ICALM.

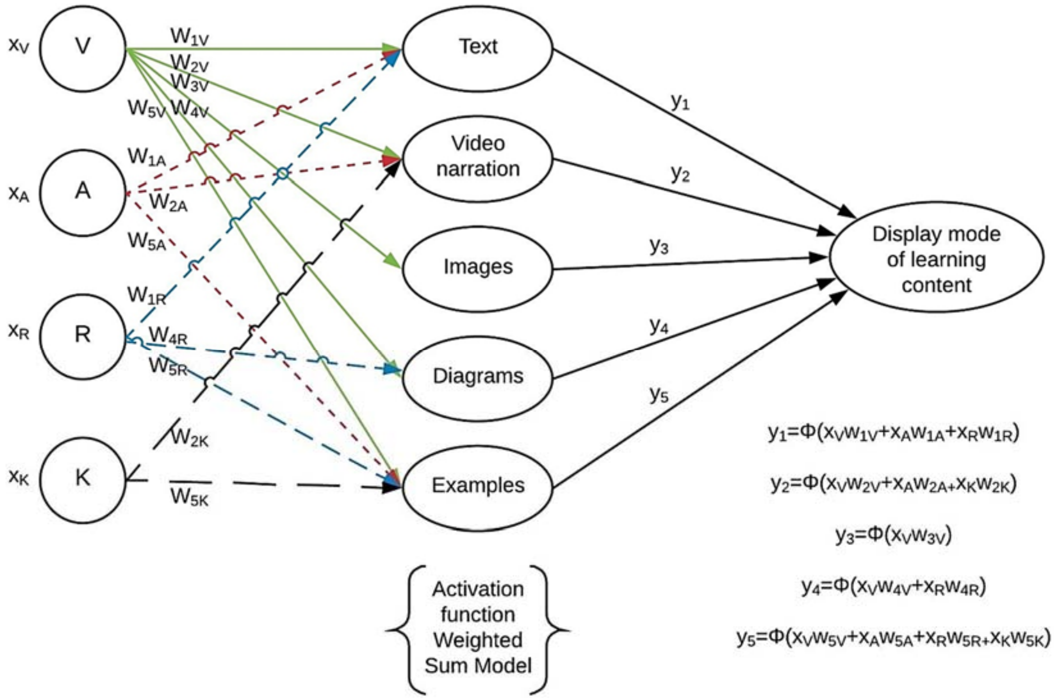

Fig. 2. Construction of the ANN with MCDA.

The weights in the ANN have been defined by 14 professors and teachers (3 teachers of primary school, 5 teachers of secondary school and 6 university professors) of different knowledge domains. Each of these 14 tutors has at least 14 years experience in educational process and instruction. However, the defined weights of the presented ANN can be changed according to the preferences of each particular tutor. Let's see an example of operation of the presented ANN. Mike is a student that his learning style is 70 % Reading and 30 % Visual, according to the system's classification. So, XV=0.3, XA=0, XR=0.7 and XK=0. The values of the corresponding weights of our ANN are the following: W1R =0.8, W4R =0.1, W5R =0.1, W1V =0.1, W2V =0.2, W3V =0.3, W2V =0.3 and W5V =0.1. According to the activation function that is based on WSM, we have the following results:

$y_1 = 0.3 \times 0.1 + 0 + 0.7 \times 0.8 = 0.59$
$y_2 = 0.3 \times 0.2 + 0 + 0 = 0.06$
$y_3 = 0.3 \times 0.3 = 0.09$
$y_4 = 0.3 \times 0.3 + 0.7 \times 0.1 = 0.03 + 0.56 = 0.16$
$y_5 = 0.3 \times 0.1 + 0 + 0.7 \times 0.1 = 0.1$

From the above results, the system concludes that the content of the domain concept, which is going to be delivered to Mike, has to be displayed, manly, with text, which will include some diagrams. Regarding the partitioning of students' learning style, it is specified using the k-means clustering algorithm. The goal of this algorithm is to find groups in the data. The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity. Each centroid of a cluster is a collection of feature values which define the resulting groups. More analysis on k-means algorithm in the context of e-learning is presented in the authors' previous research work [31].

4. Evaluation

The evaluation is a core phase in the systems development life cycle since it measures the effectiveness of the system and seeks potential enhancements. Then, the evaluation provides metric for the success of the software. Even though there are several frameworks and questionnaires that can be used in the evaluation study. There is not any standard agreed approach for evaluating adaptive learning material delivery. Hence, for the evaluation of ICALM, we have created a questionnaire that includes questions that examines the user experience, learning results and system efficiency. The questions were close-ended based on Likert scale with the responses ranging from "Unsatisfactory" (1) to "Excellent" (5). The questionnaire is depicted in Table 1.

For the evaluation study, two fully operating e-learning systems have been used: 1) a web-based educational application for programming languages tutoring and 2) a web-based e-learning system for English and French language tutoring. Examples of operation of these two systems, using ICALM, attests that ICALM is proved to be effective for optimizing e-learning, while providing great assistance to learners in a computer-aided instruction environment. In particular, 25 students used the first system and 30 students used the second system. They used the systems for a period of 6 weeks. The students were assisted during the whole evaluation process by 3 instructors and the evaluators. The contribution of the instructors in the evaluation was very important.

Fig. 3 illustrates the results of the three aforementioned categories of questions. These results include the average of answers of 55 students. The results of each category depict an average score of the questions belonging to each category. In all categories, ICALM seems to achieve great scores since it constructs a personalized and adaptive learning environment where students are engaged in learning and upgrade their knowledge by making use of all its modularities.

Table 1. Questionnaire.

User experience	Q1	Is the user interface friendly?
	Q2	Did you like the domain knowledge units?
	Q3	Is your opinion about the tutoring process positive?
	Q4	Rate your experience during the tutoring process.
Learning results	Q5	Do you feel that you upgraded your knowledge during the tutoring process?
	Q6	How accurate are the learning objectives?
	Q7	How accurate is the identification of you knowledge level by the system?
System efficiency	Q8	Were you self-assured during the tutoring process?
	Q9	Do you believe that the domain knowledge units corresponded to your knowledge level?
	Q10	Do you feel that your lack of knowledge was properly handled by the system?
	Q11	Do you feel that the system was adapted to your knowledge level?
	Q12	Do you feel that the system was adapted your learning needs?

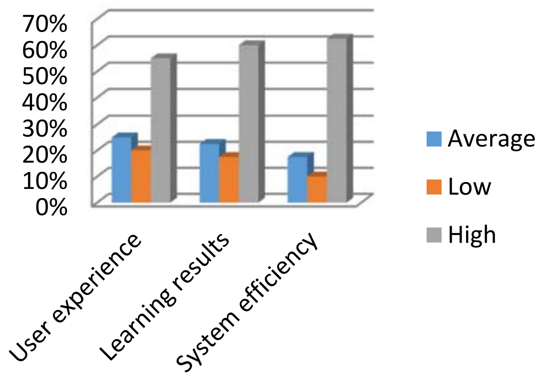

Fig. 3. The evaluation results.

For the evaluation study, we used t-test to further improve the results. As mentioned above, our presented approach was fully incorporated into a web-based educational application for programming languages tutoring (PLTS). Then, this system was compared to it conventional version. Specifically, the conventional version did not employ our intelligent mechanism to create and adapt dynamically the learning material on the fly, taking into consideration each time the needs and abilities of each individual learner. At this phase of the evaluation, 40 students participated. 20 of them (group A) used the web-based application for programming languages tutoring (PLTS) and the other 20 students (group B) used its conventional version.

According to Table 2, we can infer that Questions 2, 5, 7, 9, 10 and 11 present a statistically significant difference. That means that the system empbodying our intelligent mechanism is more sophisticated than the conventional version and can create a more personalized and adaptive environment for the learners.

Table 2. T-test results.

	Question 2 for PLTS/Conventional system		**Question 5 for PLTS/Conventional system**		**Question 7 for PLTS/Conventional system**		**Question 9 for PLTS/Conventional system**		**Question 10 for PLTS/Conventional system**		**Question 11 for PLTS/Conventional system**	
	Group A	Group B	Group A	Group B	Group A	Group B	Group A	Group B	Group A	Group B	Group A	Group B
Mean	7.588	6	7.941	5.353	6.765	4.177	6.294	3.941	6.647	4.412	8.235	5.294
Variance	2.132	0.25	3.309	0.743	1.441	1.029	2.346	0.809	2.492	0.757	0.941	0.471
Observations	17	17	17	17	17	17	17	17	17	17	17	17
Pooled variance	1.191		2.026		1.235		1.577		1.625		0.706	
Hypothesized Mean Difference	0		0		0		0		0		0	
df	32		32		32		32		32		32	
t Stat	4.243		5.302		6.789		5.46		5.112		10.206	
P(T<=t) one-tail	8.82E-05		4.13E-06		5.64E-08		2.59E-06		7.17E-06		6.86E-12	
T Critical one-tail	1.694		1.694		1.694		1.694		1.694		1.694	
P(T<=t) two-tail	0		8.26E-06		1.13E-07		5.17E-06		1.43E-05		1.37E-11	
t Critical two-tail	2.037		2.037		2.037		2.037		2.037		2.037	

In more detail, the intelligent system performs better that its conventional version in terms of acceptance of knowledge level units, students' knowledge level upgrading, accuracy of the identification of the knowledge level, correspondence between domain knowledge and knowledge level, appropriate handling of the lack of knowledge and adaptation to the knowledge level of students. These results were expected, since the system employing our intelligent approach given that the intelligent version employs artificial neural networks, multi-criteria decision analysis and machine learning techniques in order to build an individualized learning environment.

5. Conclusions and Future Work

In this paper, an intelligent mechanism, which is called ICALM that allows an adaptive learning system to create and adapt dynamically the learning material on the fly, is presented. ICALM takes into consideration each time the needs and abilities of each individual learner and adapts the learning material that is addressed to the learner at three levels: 1) Knowledge level; 2) Content of the learning material, and 3) Display mode of the learning content. ICALM uses a combination of Artificial Intelligence techniques in order to manage to adapt the learning material that is addressed to a particular learner to her/his knowledge level, abilities and needs. These techniques are an artificial neural network and the machine learning techniques of the k-means clustering algorithm, the String Matching algorithm and the String Meaning Similarity technique. Furthermore, our system uses the Weighted Sum Model, which is a method for multi-criteria decision analysis. The aim of the presented system is to use proficiency and determine what a student really knows and to accurately and logically move students through a sequential learning path to prescribed learning outcomes and skill mastery. The presented mechanism was fully incorporated in two adaptive e-learning systems (for programming language and for foreign languages). Furthermore, a wide-range evaluation, which included questionnaire and t-test, was conducted. The evaluation results showed that ICALM provides great assistance to learners in a computer-aided instruction environment.

It is in our future plans add to the presented artificial neural network the ability to be self-trained, in order to be able to adjust itself the values of the weights. This can be done in the future due to the fact that we will have in our disposal a large amount of data from the system's application in e-learning systems.

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