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Providing dynamic adaptivity in Moodle LMS according to Felder-Silverman model of learning styles

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Abstract: *E-learning as a difficult structure contains distance learning, teaching resources in many forms and shapes, group and individual learning procedures, as well as interactive and tuition work. In order to increase the use and efficiency of e-learning systems, it is necessary to consider the individualities of students and their learning styles. Based on data collected in various ways, research methods Felder-Silverman Index of Learning Style Questionary (ILS), using the Moodle LMS, based on the subjective valuation of teachers, as well as based on data from the corporate information system, the affinities of students are determined. Then, based on this information, an adaptation is made, a process that adjusts the work of the LMS based on the learning styles of the students. The major goals that can be achieved by dynamic adaptation the e-learning system are to improve the appearance and effectiveness of the course, support in finding information about the subject, more efficient search and placement of search results in terms of student's interest, and rise students faithfulness to the educational institution.*

Keywords: *e-Learning, ILS Questionary, Learning Style, Moodle LMS, Dynamic Adaptation.*

1. INTRODUCTION

Computer-based learning has become commonplace in the modern age. Many distance learning systems distribute educational resources on the Internet and indeed entire study programs are now widely available on the Internet. Such a large amount of content and information can be intimidating for students, who may exhibit a variety of individual characteristics, such as variations in goals, interests, motivation, and / or learning preferences. This suggests that a uniform learning environment approach to delivering materials and resources to students is not appropriate and that personalizing such materials / resources should address student differences to provide a tailored learning experience, increasing its efficiency by reducing dropout rates and maintaining high student motivation [1], [2].

Over the last 2-3 decades, e-learning software systems have become the main means of achieving various goals, mostly related to supporting or even completing the learning process. Their use is already a good practice in almost all areas of education and business. They are not limited to supporting educational institutions and corporate structures, but also small and medium-sized enterprises and individuals [3], [4].

Adaptive tools built into software systems for e-learning are the main methods for achieving effective results of the offered education, i.e. providing maximum assimilation of necessary skills by students, achieving it in less time, offering an environment for lecturers to create courses, manage the whole process, etc. [5].

The development of scientific and technological progress and the processes of globalization and the removal of obstacles to the international exchange of information enable the provision of various services in education, as well as access to them. The main goal for autonomous increase of the e-learning effect is achieved by using adaptive tools. On the other hand, existing e-learning software systems offer general functionality and a small number of specific adaptive tools [6].

This paper examines the creation of a dynamic adaptive e-learning system at Moodle LMS, paying special attention to the preferred learning styles of students in accordance with Felder-Silverman model of learning styles (FSMLS).

2. FELDER-SILVERMAN MODEL OF LEARNING STYLES

In Felder-Silverman model of learning styles, students are characterized by values in four dimensions. These dimensions are based on the main dimensions in the field of learning styles and can be viewed independently of each other. They show how students prefer to process (Active-Reflective), perceive (Sensory-Intuitive), receive (Verbal-Visual) and understand information (Sequential-Global). Although these dimensions are not new in the field of learning styles, the way they describe the student's learning style can be seen as new [7].

While most learning style models, which include two or more dimensions, derive statistically predominant types of students from these dimensions, Felder and Silverman describe learning styles using scales from -11 to 11 for each dimension (including only odd values). Therefore, each student's learning style is characterized by four values between -11 and 11, one for each dimension. These scales facilitate a more detailed description of learning style preferences, while building student types does not allow for differentiation of preference strengths. In addition, the use of scales allows the expression of balanced preferences, which indicates that the student does not have special preferences for one of the two poles of the dimension. Moreover, Felder and Silverman consider the resulting tendencies to be tendencies, meaning that even a student with strong preferences for a particular learning style may sometimes act differently [7], [8].

The active-reflective dimension is analogous to the corresponding dimension in Kolb's model [9]. Active students learn best by actively working with learning materials, applying materials, and trying things out. Moreover, they are more interested in communicating with others and prefer to learn by working in groups where they can discuss the material learned. They often use various forums to study new information. In contrast, reflective students prefer to think about the material and think about it. When it comes to communication, they prefer to work alone or in a small group.

The Sensory-Intuitive dimension is taken from the Myers-Briggs Type Indicator and also has similarities to the Sensory-Intuitive dimension in Kolb's model [10]. Students with a sensory learning style like to learn facts and concrete learning material, using their sensory experiences in certain cases as the primary source. They like to solve problems with standard approaches and also tend to be more patient with details. Moreover, students who hear are considered more realistic and reasonable; they tend to be more practical than intuitive students and like to connect learned material with the real world. This type of individual prefers to solve problems with known methods whose effectiveness has already been proven and

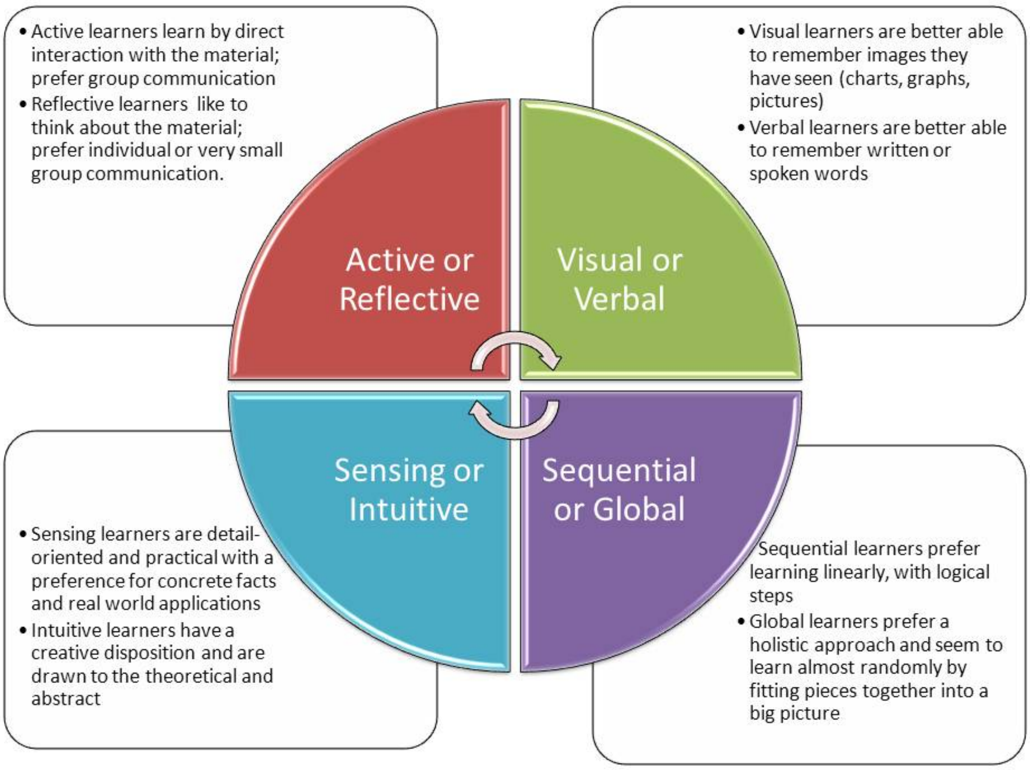

Figure 1. *Four dimensions of FSMLS* [7]

do not want to face some unforeseen obstacles and difficulties. They go into detail and try to remember more facts. In contrast, intuitive students prefer to use abstract learning material, such as theories and their basic meanings, with general principles rather than concrete examples being the preferred source of information. They like to discover opportunities and relationships and tend to be more innovative and creative. Therefore, they have a better result in open tests than in single-answer tests [11].

Third, the Visual-Verbal dimension deals with the preferred mode of input. The dimension distinguishes students who best remember what they saw (e.g., pictures, diagrams, flow charts, tables, animations, etc.) from students who receive more than textual presentations, whether written or spoken [12].

In the fourth dimension, students distinguish between sequential and global ways of understanding. This dimension is based on Pask's model of learning style [13], where sequential students refer to serial students and global students refer to holistic students. Students in this category prefer learning from smaller sequences and need templates to navigate the curriculum. The educational process is viewed as a whole consisting of small steps, and each of the steps is interconnected. In contrast, global students use the process of holistic thinking and learn by leaps and bounds. They tend to absorb learning material almost randomly without seeing the connections, but after learning enough material they get the whole picture at once. Then they are able to solve complex problems and put things together in new ways; however, they have difficulty explaining how they did it. Since the whole picture is important for global students, they are more interested in reviews and broad knowledge, while sequential students are more interested in details [7], [11], [12].

To identify based FSMLS, Felder and Soloman has developed the Learning Styles Index - ILS [14], a 44-item questionnaire. As mentioned earlier, each student has personal preferences for each dimension. These settings are expressed in values between -11 to 11 per dimension, with steps - / + 2. This range comes from 11 questions asked for each dimension [6].

ILS questionnaire is a widely used and well-researched tool for identifying learning styles. Felder and Spurlin [15] provided an overview of studies analyzing response data in the ILS questionnaire regarding the distribution of preferences for each dimension, as well as verifying the reliability and validity of the instrument. Although there are several studies [16], [17], [18] that have raised open questions such as poor reliability and validity, as well as dependencies between some learning styles, Felder and Spurlin concluded that the ILS questionnaire is reliable and valid. instrument and suitable for identifying learning styles according to FSMLS [15].

3. PROPOSED DYNAMIC ADAPTIVE ALORITHM

This section describes our automatic approach to updating student models and adjusting course delivery to their preferred learning styles. Model specifications and assessment tools will be explained in subsection 3.1. and subsection 3.2 will then show how this model is built into dynamic adaptive algorithm.

3.1. Model of Learning Style

So, we focus on FSMLS. The model describes students' preferred learning style, distinguishing between preferences in four dimensions ("processing", "receiving", "perceiving" and "understanding").

There are strong arguments for removing the bipolarity of this model, and instead the model has eight dimensions instead of four. However, we decided to use the original model as it is widely accepted and well justified in the original paper [7]. An active and reflective style is the opposite and it is believed that a person will not be both very active and very reflective. Model is similar for other dimensions.

Felder and Solomon, formed a score list for the ILS questionnaire as shown in Figure 2. and a procedure for calculating student scores consisting of the following [14]:

- Put "1" in the appropriate places in the table below, for example, if the student answered "a" to question 1, put "1" in column "a" next to question 1, but if he/she answered "b" for question 1, put "1" in column b. The answer to each question should be "a" or "b";
- Gather all the units under each column and enter the sum in the indicated spaces;
- Subtract the smaller total number from the larger one for each of the four scales;
- Enter the result of the difference, which will be a number between 1 and 11, and then write the letter "a" or "b" for which the total number is higher in the lowest order.

For example, in the column for Active-Reflective Learning Style (AST-REF) if the student answered 3 questions "a" and 8 questions "b", the answer would be the difference between 8 and 3, which is "5" and "b "Because we have more 'b' than 'a.' Then we would write in the lowest row below the column AST-REF "5b". This means that the student has a moderate preference for Reflective Learning Style (5b) which is reflected within the AST-REF dimension.

The result of the evaluation of the ILS questionnaire is a set of four points, one for each dimension.

ACT/REF			SNS/INT			VIS/VRB			SEQ/GLO		
Q	a	b	Q	a	b	Q	a	b	Q	a	b
1	___	___	2	___	___	3	___	___	4	___	___
5	___	___	6	___	___	7	___	___	8	___	___
9	___	___	10	___	___	11	___	___	12	___	___
13	___	___	14	___	___	15	___	___	16	___	___
17	___	___	18	___	___	19	___	___	20	___	___
21	___	___	22	___	___	23	___	___	24	___	___
25	___	___	26	___	___	27	___	___	28	___	___
29	___	___	30	___	___	31	___	___	32	___	___
33	___	___	34	___	___	35	___	___	36	___	___
37	___	___	38	___	___	39	___	___	40	___	___
41	___	___	42	___	___	43	___	___	44	___	___
Total (sum X's in each column)											
ACT/REF			**SNS/INT**			**VIS/VRB**			**SEQ/GLO**		
	a	b		a	b		a	b		a	b
	___	___		___	___		___	___		___	___
(Larger – Smaller) + Letter of Larger (see below*)											
____			____			____			____		

*Example: If you totaled 3 for a and 8 for b, you would enter 5b in the space below.

Figure 2. *Score list for ILS questionnaire*

3.2. Similarity algorithm

To find similarities between the two students, we compare their data records that catalog their previous interaction with the system. We usually compare the incomplete records of the "new student" who is currently studying the object of study with the complete records of the previous student who successfully completed and passed the teaching content. There may be many "previous students" who have taken the subject. The identities of these "previous students" are kept in the "order of similarity" which is sorted according to the similarity of the record with the incomplete record of the new student to the point where the new student has reached. The order is sorted from most similar to least similar. The adaptation algorithm then searches this line to find the greatest result of the similarity between the previous and the new student in order to decide how to present the teaching content to the new student.

4. DYNAMIC ADAPTIVE LMS ARCHITECTURE

Adaptability was realized using four components: student model, content model, similarity algorithm and machine learning algorithm. When a student applies through the Moodle LMS, an ILS questionnaire is initiated that the student completes to predict their learning style. All student-specific data, learning style outcomes, current phase of learning content, average student grade, and interaction with the system are recorded in the student model. The content model approaches the learning content and presents it to the new student according to the desired dimensions of the learning style.

The teaching contents are adapted to the student's preferred learning style. After studying each concept, the student is asked to answer a series of questions in order to assess his/her understanding of the concept. If the assessment results are not satisfactory and the student does not pass the evaluation, the similarity algorithm searches the system database in search of previous learning patterns that are similar to those of this new student. Then the similarity algorithm forms a list of previous students and rearranges it, according to similarity, from highest to lowest. The similarity is not just in the student's learning style; covers the characteristics of the student, his/her time spent on the curriculum, his/her average grade and his/her learning style. Accordingly, the algorithm selects the most similar student and represents the learning content of the material adapted to his/her preferred learning style, which may not be the same as that of the previous student. This is followed by an assessment of the understanding of the newly adapted material, i.e. the presentation for the new student. If a new student passes the evaluation with a new learning style, the algorithm updates the student model with these changes. These changes will be returned to the student content model that will be used to present the next teaching material with the updated student model.

If the student does not do well the second time with the newly adapted learning styles, the algorithm selects the next student from the list of similarities. The system then presents the material to the new student with the preferred learning style of this other previous student. A new student is allowed to repeat the same material up to three times. This limits the time required for participants to participate in the experiments. If a new student does not do well in any of the three repetitions, the system chooses the best of the three outcomes to decide which learning style will be used to present the next teaching material.

Proposed adaptive system is implemented on Moodle LMS used by students attending online courses. The adaptability algorithm must be able to quickly produce an edited list of previous students in order to respond to student action and learning styles within a reasonable period of time. To achieve this, the algorithm is linked to a machine learning scheme that is able to efficiently handle student data records as the number of records grows. As the number of records of previous students increases, the efficiency of the implementation of the similarity algorithm becomes increasingly important. Algorithm must be able to process records quickly to identify similar behavioral learning styles among students. To achieve this efficiency, a classification algorithm is used to identify and parameterize similar patterns in records. This is one of the advantages of the proposed system, i.e. increasing the performance and accuracy of the system compared to similar adaptive systems, which are complex and expensive [19].

The advantage of the proposed system over other adaptive systems is that it does not involve any additional work for students other than completing the ILS questionnaire at the beginning. Students do not have to play any role in choosing the desired learning path and are not required to give opinions or grades that may confuse and distract them. Our proposed adaptive system adapts student learning styles to suit their actions during the course and periodically updates the student model.

4.1. MySQL system database

MySQL is used to access the records of previous students. These records document the usage, behavior, learning styles, and labels stored in the Moodle LMS database. To extract student data, we used MySQL (Figure 3.), a tool for database administrators. This tool helps us to visualize, delete, edit and modify database tables.

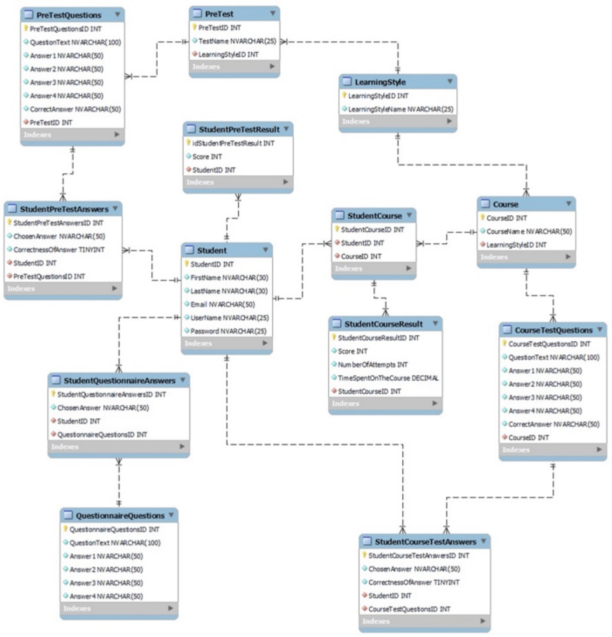

Figure 3. *MySQL diagram for adapted Moodle LMS*

4.2. User interface design

This subsection describes the user interface and guidelines that have been considered for our e-classroom design. The first interface presented to the student is the application for the e-classroom, followed by the interface for registration of class attendance and filling in the ILS questionnaire and answering the test questions. After that, the graphical user interface is customized in the teaching content section with presentation options depending on whether the system needs to be unadaptable or dynamically adapted. The graphical user interface is designed in a simple way, to help students navigate the system easily.

4.3. Adaptive Moodle LMS - Implementation phase

The implementation phase has extended the standard version of Moodle LMS. Moodle LMS has been expanded in line with the link between learning styles and educational materials, and in line with customized content, as shown in Figure 4.

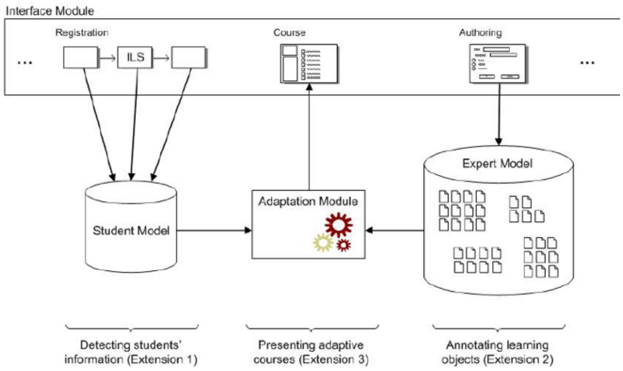

Figure 4. *Moodle LMS architecture extensions*

The first extension deals with the ILS questionnaire and test for assessing students' initial knowledge and initialization. The ILS questionnaire and test questions were added to the registration form in Moodle LMS. The results of learning styles from the questionnaire and the results of the pre-test are calculated and stored in the student model.

The second extension deals with presenting the course content in an appropriate presentation that matches the learning styles preferred by the students. While the adaptation is performed according to the adaptive algorithm. Learning content is presented through a normal user interface.

The third extension allows the system to dynamically update student profiles in a reasonable amount of time. The proposed method of adaptation is based on the similarity algorithm using the machine learning algorithm - the decision tree.

5. EXPERIMENT SAMPLE

90 students of Alfa BK University participated in our experiment, while 77 students fulfilled the conditions of the experiment, namely 33 students of Faculty of Finance, Banking and Revision, 24 students of Faculty of Foreign Languages and 20 students of Faculty for Management in Sport. According to the results for the population of 90 students at the confidence/reliability level of 95% and the margin of error of 5% is estimated at 74 participants. Therefore, the sample size of our experiment is statistically significant for testing our hypotheses.

6. CONCLUSION

Intelligent learning systems diagnose the learning process and generate instructions and learning content during the implementation of the program, mainly based on the results of students in problem solving. Building a personalized learning path is one of the areas where there is a clear link between hypermedia and intelligent adaptive e-learning systems.

If teachers have information on the way in which students learn most easily, or they have information on their learning style, they will have additional indications on how to prepare the teaching content and in what format to convey it to students. This will make the listeners more motivated and active, which leads to easier learning of the teaching content.

The adaptive learning software system aims to adapt some of its key functionalities (i.e. providing learning content, supporting navigation in the training course, etc.) to the needs and preferences of students. In that sense, adaptability can be seen as the ability of the system to adapt its behavior and provide its functionality to users according to their preferences, educational goals, learning style, level of knowledge, behavior in the system, etc.

As part of the conducted experiment, the effects of the control, static and dynamic groups were statistically examined in relation to the set research hypotheses. The results showed that there is a statistically significant correlation between the progress of students on the post-test in relation to the result achieved on the pre-test in relation to the group to which the student belongs. A significantly better result on the post-test was achieved by students from the dynamic group compared to students from the static and control groups. Also, it was determined that students from the dynamic group spend less time on the course compared to students from the static and control groups, i.e. it was determined that students from the dynamic group spend significantly less time answering questions on the final test compared to students from statistical and control groups.

The overall results of the experiment were useful and encouraging. It was confirmed that the topic of the case study was new to all participants and, being purely from the ICT field, proved to be of potential interest to them. The students' opinions about the design and implementation of the adaptive Moodle LMS were that it was clear and understandable.

It is evident from this study that dynamically adaptive LMS can motivate students and improve their learning outcomes. However, more research is needed to investigate and study the learning styles of students in an e-learning environment to find out what factors influence their achievement. A better understanding of students' learning styles may eventually lead to the widespread acceptance and use of adaptive algorithms in e-learning systems that can provide effective and practical adaptive systems.

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