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E-learning based on the adaptive learning model: case study in Serbia

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Abstract. Today's education faces many challenges related to learning and teaching efficiency, effectiveness, and costs. Contemporary research shows that the learning environment with the ability to adapt to individual needs, requirements, and competencies of students, facilitates the learning process and leads to improved learning outcomes and achievements. Nevertheless, learning management systems (LMS) that are often used in e-learning typically provide a limited level of adaptivity. The goal of this paper is to introduce an adaptive e-learning model which enables personalized learning experience and more intelligent decision making. It consists of the students' model, the adaptation module, the expert system for data analysis and decision making, the repository of learning objects, and database of educational methods. The designed model provides adaptivity through a learning management system, considering individual characteristics of the student, such as their learning styles and prior knowledge. It is capable to adapt course content, structure, and assessment based on the specific student's needs and performance. The model is implemented within the widely used open-source LMS, which makes it more usable and easier to deploy. The process of applying the proposed model is illustrated with a higher education case study that shows how the recommended method is applied for a successful transition to an adaptive form of learning. The model has been tested through experiment during which a group of students attended traditional non-adaptive e-learning course, and the other group attended the adaptive e-learning course. The results of data analysis showed that students who learned from an adaptive course achieved better performance in various aspects. The proposed adaptive model can enhance educational processes in terms of improving learning performance, personalized application of teaching/learning methods, as well as continuous improvement cycle.

Keywords. Adaptivity; learning management systems; e-learning; expert system; data analysis.

1. Introduction

Over the past decades, the impact of Information and Communication Technologies (ICT) on education was extraordinarily high, which has led to the introduction of new forms of learning assisted by the employment of computers and the Internet. It can be sad that e-learning is a product of the modernization of education and learning.

E-learning courses can exist in different forms, using different types of technologies, and they are usually published online through a learning management system (LMS) [1].

The present-day instructional design focuses on providing a variety of tools to sustain learning in a more convenient, flexible, personalized, and on-demand mode. The phrase "adaptive learning" implies the ability to vary, change and to modify consistent with any learning competencies of a student, as a function of information which is obtained through their execution on set tasks or assessments [2]. The personalized learning environments that offer a high level of adaptation to students' needs and preferences are the future of e-learning systems [3].

Adaptive learning is a method for providing personalized learning, with a tendency to make available competent, successful, and tailored learning pathways for engaging each student [4]. Adaptive LMSs use a data-driven and, in some cases, a nonlinear approach to instruction [5]. They dynamically adapt to student interactions and levels of ability and performance, delivering certain types of educational content and learning materials in the appropriate order and sequence that students need, and at specific times to make further progress in learning [6].

Adaptivity is an important issue in e-learning however, LMS that incorporate adaptivity are rare. Not many studies have been carried out dealing with creating adaptive systems which aimed at providing personalized courses tailored to the individual needs and characteristics of students. Research on adaptivity in e-learning is usually focused

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either strictly on the pedagogical aspect (forms and methods of work, specific requirements, sensitive groups of students, etc.) [7] or on the technical aspect (LMS structure, algorithms, queries, approaches and techniques for platform improvement, etc.) [8].

The approach presented in this paper stresses the importance of the symbiosis of two key approaches - pedagogical and technical. Because only by respecting and fulfilling the characteristic, both pedagogical requirements of adaptive learning, as well as technical requirements, possibilities and limitations of the platform, it is possible to achieve the maximum effect in the personalization of the education process [9]. Another characteristic of the presented approach is the adaptation of the learning process on two pedagogical dimensions: based on the student's prior knowledge, and according to the preferred learning style. Most of the existing research studies, take into consideration only one dimension (usually by one particular student feature – learning style, prior knowledge or some special need, etc.).

In this paper, a specific adaptive learning model with main components, and its software realization are presented. The model has been designed, taking into account the constraints of the existing e-learning platforms, and offers a high level of adaptivity, personalization, and flexibility. It can be applied for diverse groups of students that have different characteristics such as learning styles and prior knowledge. The model has been implemented in the open-source Moodle LMS. The results from the experiment demonstrate the applicability and effectiveness of the proposed model.

The paper is organized as follows. The Background Research section provides an overview and brief analysis of the existing research results and approaches in the field of adaptive learning. The Materials and Methods section describes the design and implementation of an adaptive model for e-learning. In this section, the methodology of the conducted experiment is also presented. The next two sections are related to data analysis using various statistical methods, and discussion of the obtained results. The Conclusion section summarizes the research results, advantages of the proposed model, and gives future research directions.

2. The background research

Research in adaptive systems can be traced back to the end of the last century (the early 1990s). At that time, the two main areas – hypertext and user modelling, created many new research ideas as a result of various improvement they have achieved. Numerous research teams have recognized static hypertext problems in different domains and had begun to reconsider other ways of modifying the behaviour of hypertext systems to users in an individual way [10].

Nowadays, e-learning researches are focused on learning platforms that take into account student's preferences, like: learning styles, habits, expectations, motivation and other characteristics of personal needs [11]. These factors draw attention to the idea of adaptive learning systems as an alternative to the usual, "one-size-fits-all" approach in a traditional educational environment [12]. The authors define adaptivity as the ability of a system to adjust its behaviour to the students' needs and other characteristics [13].

Existing adaptive web-based educational systems such as AHA, APeLS, and 3DE offer varying degrees of adaptivity [14–16]. Moreover, they have some strict restrictions such as: supporting a small number of e-learning options, lack of integration, learning contents that can not be reused, etc. These are one of the greatest reasons for the low usage of such systems.

On the other hand, typical LMSs such as Blackboard, WebCT or Moodle, which are often and successfully used in e-learning (because they offer numerous options that support teachers to create and handle their online courses) provide a low level or no adaptivity at all [17].

The ability to adapt learning content to student performance and progress may be a key issue for the learning process [3].

Three types of adaptivity can be defined [18]:

- Adaptivity of the learning contents based on students' preferences (needs, educational background, skills, and experience, etc.) This kind of adaptivity usually means that learning content is personalized according to the preferred learning style of the student.
- Adaptivity of presentation mode and forms of educational and learning content (it is assumed that the content for learning is in a certain form of personalized learning sequences of educational objects).
- Complete adaptivity (which is a mixture of the preceding two types).

There are several adaptation techniques, however, most frequently support for adaptive presentation and adaptive navigation support [19]. The adaptive presentation involves adaptation of features based on content (adaptive text and/ or multimedia presentation). Adaptive navigation is grounded on a variety of connectivity modes and linking (adaptive taxonomy, straight guidance or hiding and annotating of links). Another aspect of adaptivity includes what type and kind of data concerning the student are employed as a foundation for the adaptation. Adaptivity can be provided depending on different characteristics and needs of the student (prior knowledge, skills, and competencies, learning goals or students learning styles) [20–23].

Analysing adaptivity in an e-learning system has expressly found out the importance of the modelling psychological feature and cognitive characteristics of the student, particularly learning style as the most studied cognitive feature [24]. There are several different models of learning style presented in the literature [25] however, Felder-Silverman Learning Styles Model (FSLSM) is usually used to ensure adaptivity in respect of learning styles in e-learning environments. Most other learning style models classify learners in few groups, whereas FSLSM describes the learning style of a student in more detail, distinguishing between preferences on four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global [26].

Felder and Silverman [23] claim that students learn in numerous, different ways: by hearing and vision; by reflecting and acting; thinking logically or intuitively; by memorizing spoken/written materials and remembering seen images; and, either steady, in small steps or in large leaps (figure 1).

FSLSM distinguishes four dimensions, i.e., four learning styles depending on student preferences. A description of these dimensions is detailed and given in the numerous papers and studies, but here we refer to papers [28] and [26]:

(i) The first dimension inspects the student's desired method of processing information: active or reflective. Active learners work well in teams. They dont learn much in situations that request them to be passive and they are more likely to be experimentalists. On the contrary, reflective learners work better on their own or with one other person at most. They dont learn much in situations that dont enable them a chance to think about the given data and presented information, and they are more likely to be theoreticians.

(ii) The second dimension considers the type of information that the learner prefers: sensory or intuitive. Sensory learners like better to learn facts and they like teaching material associated with practical situations from the real world, whereas intuitive learners prefer abstract learning material such as theories and their fundamental meaning. Intuitive learners are easier with symbols than sensory learners.

(iii) The third dimension considers the sensory channel through which the learner perceives external information with most success: visual or verbal. Visual learners prefer pictures, diagrams, graphs, or

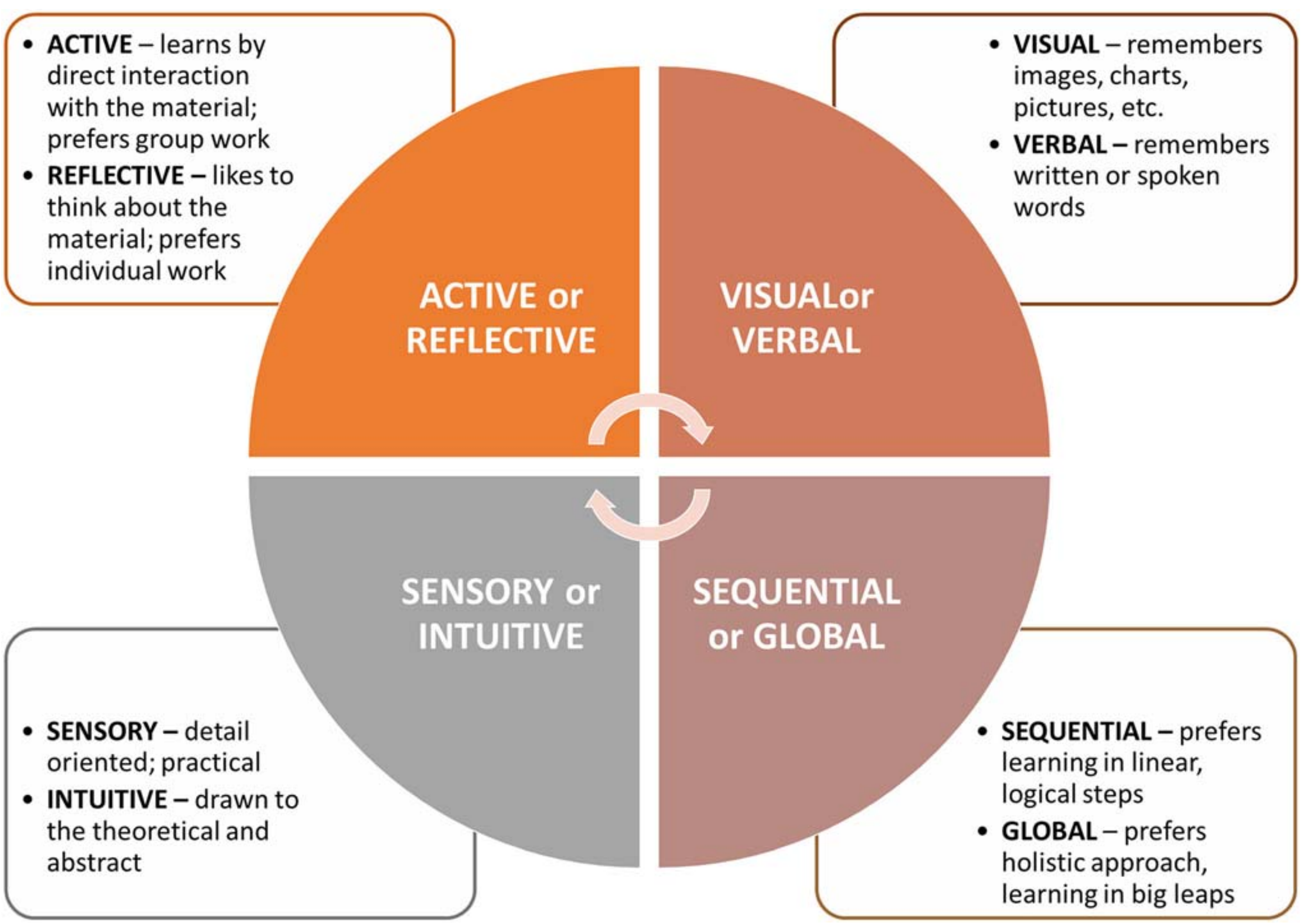

Figure 1. Felder-Silverman's model [27].

presentation, while verbal learners like spoken information or audio record.

(iv) The fourth dimension considers how the learner progresses toward understanding: sequentially or globally. Sequential learners learn in small steps, and therefore have linear progress in learning, aspire to follow logical step-wise paths and methods to solutions. On the other hand, global learners use a holistic thinking process and learn in large leaps. They tend to understand learning materials nearly accidentally without spotting connections between them; however, after studying enough and adequate learning material, they rapidly perceive the complete image. They can solve complex problems, make and put things together in new, original ways but it's troublesome for them to explain how they did it.

When these four dimensions, i.e., learning styles, are considered, as well as their characteristics, it can be understood why this classification is the most prevalent for recognizing learning styles in e-learning. Characteristics of each dimension can be covered by a certain format and form of digital educational materials (texts, essays, multimedia presentations, audio-video recordings, simulations, etc.). Also, the form of the instruction model itself can be algorithmically implemented step by step, while respecting all the characteristics of a certain, defined, learning style. For example, a comparative study by Zine *et al* [29] confirms the advantages of FSLSM model in e-learning over the other models for identification and classification of learning styles.

As such, FSLSM is used in various research fields related to personalization of learning. This includes papers investigating the importance of personalized e-learning in terms of interrelation between Index of Learning Styles and academic achievement [30], and the use of FSLSM for online courses design [31]. Some authors propose an architecture of adaptive online module system for learning, where adaptivity is based on a students' learning style defined and classified according to FSLSM [32]. Other authors consider the most optimal form and profile of learning objects (i.e., educational materials, methods, forms of work, and ways of their delivery to students), depending on the recognized learning style of students, where FSLSM is used for its detection [33].

Personalization of learning, in a pedagogical sense and an ideal educational environment, implies adapting the learning process to the needs of students (learning styles, prior knowledge, psycho-physical disabilities, if any, social background, special talents, etc.). One of the main limitations of the existing approaches to adaptivity is that they usually consider only one of those aspects. They also lack some form of intelligent components that should automate adaptation of the course content and structure according to students' characteristics and performance, as well as efficient and effective decision making based on data analysis. Additionally, adaptive learning systems require more types of learning objects, teaching and assessment methods, interaction channels, etc., in order to enable personalized and adapted learning environments.

The main goal of this research is to develop an adaptive e-learning model which overcomes the deficiencies of traditional LMS and teaching/learning approaches. The idea is to design and integrate various components that enable more personalized and tailored learning and teaching. This requires components for adaptation, customized course creation/adjustments, data analytics, and improvement actions. The courses can be organized and tailored to specific groups of students. Adaptation is based on students' characteristics, such as learning styles, prior knowledge, and other relevant data.

The following sections introduce a new adaptive e-learning model that extends traditional LMS and provides more personalized e-learning and teaching.

3. Materials and methods

In order to achieve a more personalized approach to teaching and learning and more efficient and effective decision-making, an adaptive e-learning model was developed. It encompasses the LMS adaptation module, student model, repository of learning objects, database of learning best practices and methods, and the expert system for data analysis and decision making. This approach ensures necessary adaptivity and personalization, as well as continuous improvement through data-based decision making and application of adequate teaching/learning methods and best practices [34]. In order to incorporate adaptivity, the existing LMS Moodle platform was extended with the plugin that provide adaptivity based on preferred learning styles of students and on their previous knowledge.

3.1 *Design and implementation of the adaptive learning model*

The process of designing and implementing the adaptive LMS includes:

- the decisions on its implementation into the learning process,
- the design of flexible and suitable LMS structure for the given purpose,
- creation of learning objects and educational materials according to existing pedagogical/didactic principles and methodologies,
- creation or modification of the curriculum (or one of its parts processed by LMS), etc. [35].

The proposed model (figure 2) supports a combination of so-called static and dynamic personalization approaches

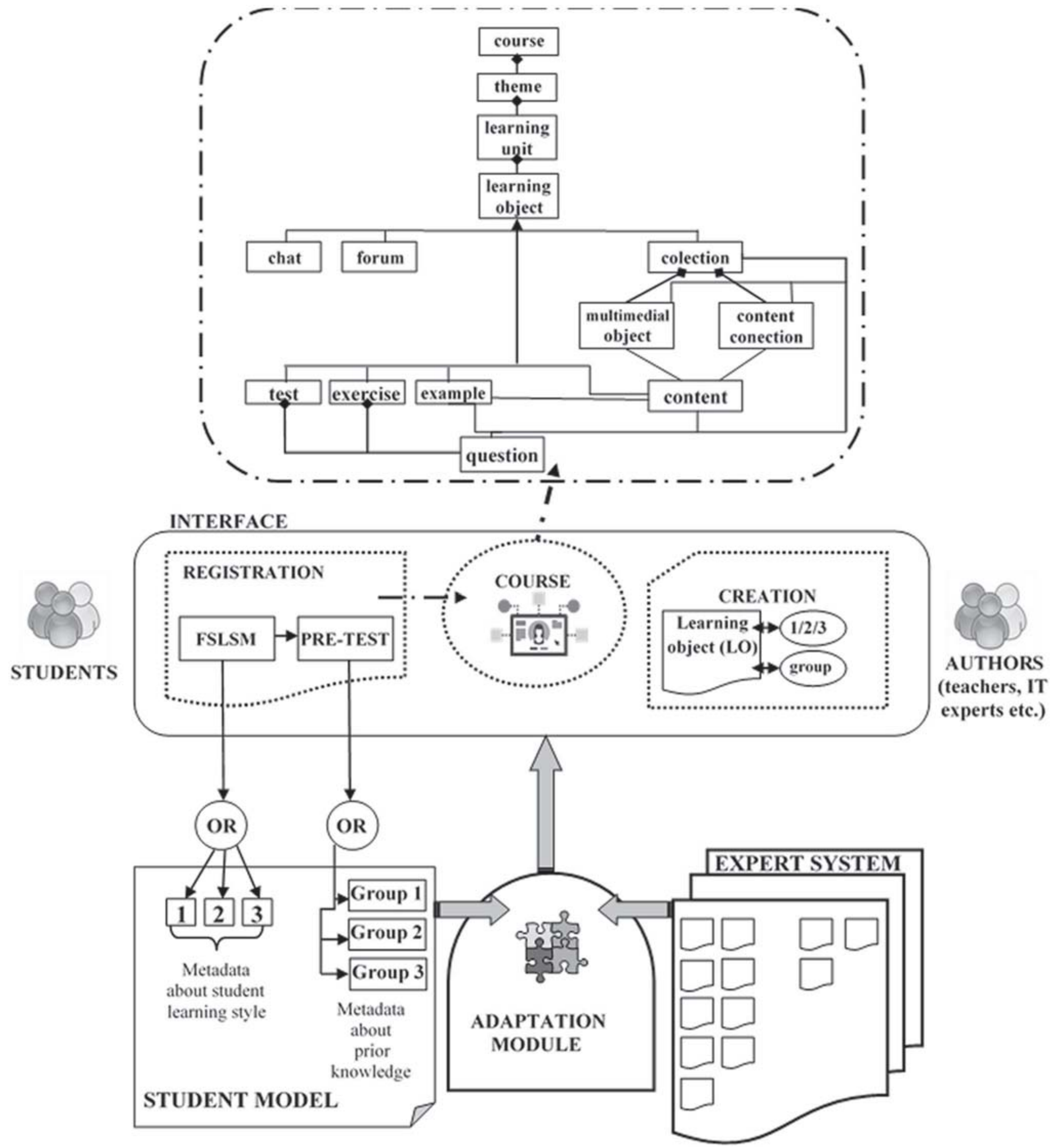

Figure 2. The Adaptive Learning Model.

[36]. The static approach is reflected in the fact that students fill in the questionnaires when they first register on the course. Based on the collected data, the system is adapted to the needs and requirements of students (such as learning style and prior knowledge). On the other hand, the dynamic approach, in the proposed model, is reflected in the constant monitoring of students' activities in real time. The obtained user data is stored in the database. Data mining of the obtained data provides useful information that can be used in future personalization of the learning processes, as well as the adaptation of teaching styles and learning materials. This combined approach provides adaptivity to new students who log in the course for the first time, and later personalization comes after

obtaining enough data on students' habits during learning [37].

The proposed adaptive learning model has been implemented within the Moodle LMS through specific the extensions (plugins). As an open-source LMS, Moodle is suitable for customization and extensions, as well as for personalization of learning. In order to provide adaptive learning, the Lesson activities were used. They enable customized and personalised learning paths, decision-making exercises, independent revisions, and subject practices.

Through the course registration, students initially complete the questionnaire, which is used to determine the preferred learning style. Thus, based on students' responses, identification of the learning styles is performed. The obtained attributes are stored in the student model. Next, students complete the specific pre-test. This test determines the level of students' prior knowledge. Based on the ability, competencies, and knowledge manifested within the pre-test, students are categorized as a beginner, intermediate, or advanced student. Metadata used for identification of the student knowledge level is stored in the students' model. Thus, through the application form, the metadata about the learning style of students and their knowledge category is obtained.

The automated response of the system, in the form of a forwarded educational materials, which corresponds to the mentioned student preferences, is realized by the adaptation module, which is responsible for accessing information about the students' learning style and knowledge category, through the student model.

Adaptation module calculates the value of every adaptation features based on the student's learning style preferences. The values of adaptation features indicate which types of personalized courses are going to be created. Besides the learning style preferences, the adaptation module also reads the metadata of the student prior knowledge category. Then, using the expert system, it accesses the appropriate elements of the course, which are further delivered to a student through the LMS front-end interface. Educational materials, which are chosen in a personalized course, must be suitable for the learning style as well as the level of students' knowledge. In order to achieve the full effect of the adaptive learning model, it was necessary to create the appropriate educational materials (i.e., lectures, quizzes, exercises, presentations, videos, wikis, etc.). During the design and development of educational materials, a special attention to pedagogical-didactic methodologies and principles was given.

By adjusting the educational course in terms of the two dimensions of the learning process (learning style and prior knowledge), it can achieve a higher level of adaptivity. This way, learning process is personalized to the needs of students, which should lead to higher acceptance of learning materials and better learning outcomes in terms of obtained knowledge and skills.

The student model is a vital component in adaptive e-learning systems. Adaptation generally involves selecting and presenting each educational activity as a function of the student's preferences, which are stored in the student model. Therefore, the student model is used to change the interaction between students and the system, in order to adapt to the personal needs and characteristics of the student.

The expert system is connected to the adaptation module and utilizes learning objects repository. It comprises the following components:

- logic module for reasoning and action recommendation;
- repository of learning objects, teaching, assessment, and communication methods and techniques;
- analytical models for various data analysis.

A logical module for reasoning and a recommendation for action can be considered as set of heuristic rules (if-then statements). All the rules in the expert system work together to define a certain environment - an adaptive educational course, which is achieved on the basis of surveying students and obtaining appropriate, necessary answers and the creation of the necessary attributes. After that, the expert system responds with one or more actions. The repository of learning objects, teaching, and communication methods and techniques is based on the use of learning objects (LOs) and different educational resource formats. The educational course offered by the adaptive e-learning system consists of one or more topics. Each Moodle LMS topic consists of one or more LOs, each of which consists of the following segments: the theoretical, the practical, the descriptive, and the evaluation segment.

The descriptive segment provides an explanation of the essence of a certain study subject. The theoretical segment contains the particular content for learning (it is represented by using activities and resources). The LOs' practical segment are activities related to clarifying and fortifying the obtained knowledge. The evaluation segment consists of activities used to assess what has been learned, such as a tasks, assignments, or quizzes.

For implementation of the expert system, certain Moodle components were used to organise educational course (course structure modules, sections, activities, lessons, quizzes, etc.). The analytical models primarily involve learning and evaluation analytics. These are the software algorithms used to predict or detect unknown patterns of the learning process, based on the data collected through the student-LMS-teacher interaction. For example, one of the models (based on the regression techniques) is used for discovering students who are at risk of failing a course/subject or even dropping out.

The expert system is a digital representation of the domain expert knowledge (declarative knowledge), problem-solving skills (procedural knowledge), and knowledge for making decisions about instructional methods.

The adaptation module is a bond among the student model and the expert system (together with learning objects, as well as teaching and assessment techniques). It combines the needs and characteristics of students with the suitable learning materials. It includes predefined adaptation rules and functions that help in selecting the appropriate learning objects from the repository and in determining when and in what form to deliver them.

The developed adaptive e-learning model aims to adapt the content, format of presentation as well as the learning paths. This model is established on a micro-adaptive approach using background knowledge of each student, as well as students' learning habits (learning styles) in order to adapt learning objects in a personalized manner.

The proposed adaptive learning model has been implemented on top of the Moodle LMS. The key components (the adaptation module, the student model, and the expert system) have been implemented as an extension (plugins) that can be installed on specific Moodle system. The educational resources (learning objects, course structure, assessments, etc.) are created within the Moodle LMS, and they are SCORM (Sharable Content Object Reference Model) compatible, which enables interoperability and reusability between various LMS. Data analytics models are built on the separate platform, but they are connected and consume data with the Moodle database. With certain rework in terms of data extraction, transformation, and loading, those models can be also reused for other LMSs.

In order to evaluate this adaptive learning model, an experiment was performed within the real faculty environment.

3.2 *Experimental design and methodology*

The experiment was carried out on a sample of second-year students (the group of Teachers' Department) and the first-year students (the group of Pre-school Teachers' Department), bachelor's studies.

During the experiment, each student needed to follow the procedures below:

- Identification of learning styles: all participants were required to complete a FSLSM (Felder-Silverman Learning Style Model) learning style questionnaire. The questionnaire was conducted in the form of an online survey. The obtained data are stored in a database, from where they were processed according to FSLSM principles and scales. According to the results of the questionnaire, the participants were classified into a specific learning style group.
- Conduction of the pre-test: the participants were asked to take a pre-test to identify their prior knowledge.
- Brief introduction: before using the online adaptive learning system, the participants had a short introductory lecture on how to operate and use the online learning system.
- Interaction with the online learning system: the participants are instructed to learn through the LMS, according to their determined group of affiliations.
- Conduction of the post-test: the participants were further asked to take the post-test to identify their learning performance. The post-test is conducted in the form of online testing to determine the potentially advanced level of knowledge, but also in the form of the final exam (to determine the level of student's educational achievements).

Pre-test and post-test were used to assess students' level of knowledge of the subject domain.

The first step in analysing the characteristics of the student was conducting a survey which determines the preferences in learning (i.e., learning styles), as well as the levels of students' prior knowledge.

The FSLSM was used for assessing the students' learning styles, as the most suitable for the analysis of learning styles in the e-learning environment. A clustering algorithm was used to create a model. This algorithm is used for the natural grouping of data, based on their attributes so that the value of attributes inside the group is similar and significantly different between groups [38]. Similar results are obtained in the case of dividing students into the two or the three groups. It was decided to divide the students into the three groups, because in that case the results are more logical, of better quality, and more consistent. Also, in the case of three groups of students, the degree of implemented adaptivity will be higher. Therefore, processing of data from the survey led to the classification of students into the three groups based on demonstrated learning styles of students: 1. visual/sequential/active (V-S-A), 2. intuitive/active/global (I-A-G), and 3. verbal/active/sequential (V-A-S).

Besides testing the student population in terms of preferences in learning and determining their matching learning style, testing on already existing knowledge was also carried out. A survey sample was made up of first-year students as well as the second-year students who were attending the introductory IT course. This study course is planned to provide students with basic theoretical knowledge about information technology (basic computer architecture, computer networks, office software packages, etc.).

Within each of the three groups of students (classified by learning style), a new classification of students according to the level of their prior knowledge was performed. According to their prior knowledge, students were classified into the three groups: 1. beginner, 2.intermediate and 3. advanced.

Students, who participated in the experiment, were classified into three groups according to the learning style, which were further divided into three groups according to the level of prior knowledge. In the end there were nine groups: 1-1 (V-S-A/beginner), 1-2 (V-S-A/intermediate), 1-3 (V-S-A/advanced), 2-1 (I-A-G/beginner), 2-2 (I-A-G/intermediate), 2-3 (I-A-G/advanced), 3-1 (V-A-S/beginner), 3-2 (V-A-S/intermediate) and 3-3 (V-A-S/advanced) (figure 3).

For each of the nine groups, based on the learning style and prior knowledge, suitable learning objects (lectures, presentations, exercises, assignments, quizzes, etc.) were created.

The pre-tests determined students' membership in a particular group, but for the purpose of experimenting with the adaptive e-learning model and data analysis, the dataset (students) has been split into the two segments (students' groups): adaptive and non-adaptive. Based on the random selection of students during their course submission, half of them have been referred to the appropriate course demonstrated their characteristics (to adapted e-learning course), and the other half is sent to an existing, traditional e-learning course, which does not support adaptivity. That way, one group of the students had the opportunity to undergo training in the adaptive and personalized educational course, while the other group used an existing platform for e-learning (non-adaptive). During the course, student's activities and performance were monitored, and the following data were obtained: number of logins in the course, the time spent on the course and results achieved (the final evaluation and assessment of the knowledge, derived from the fulfilment of commitments - exercise, tests and other coursework).

4. Data analysis and results

Statistical analysis was performed using SPSS software package. Continuous variables were presented as a mean ± SD. Comparisons between two groups were analysed by unpaired Student's t-test. Comparisons between more than two groups were done using the ANOVA statistical model. To determine the influence of the variables on the marks of students the multivariate linear regression

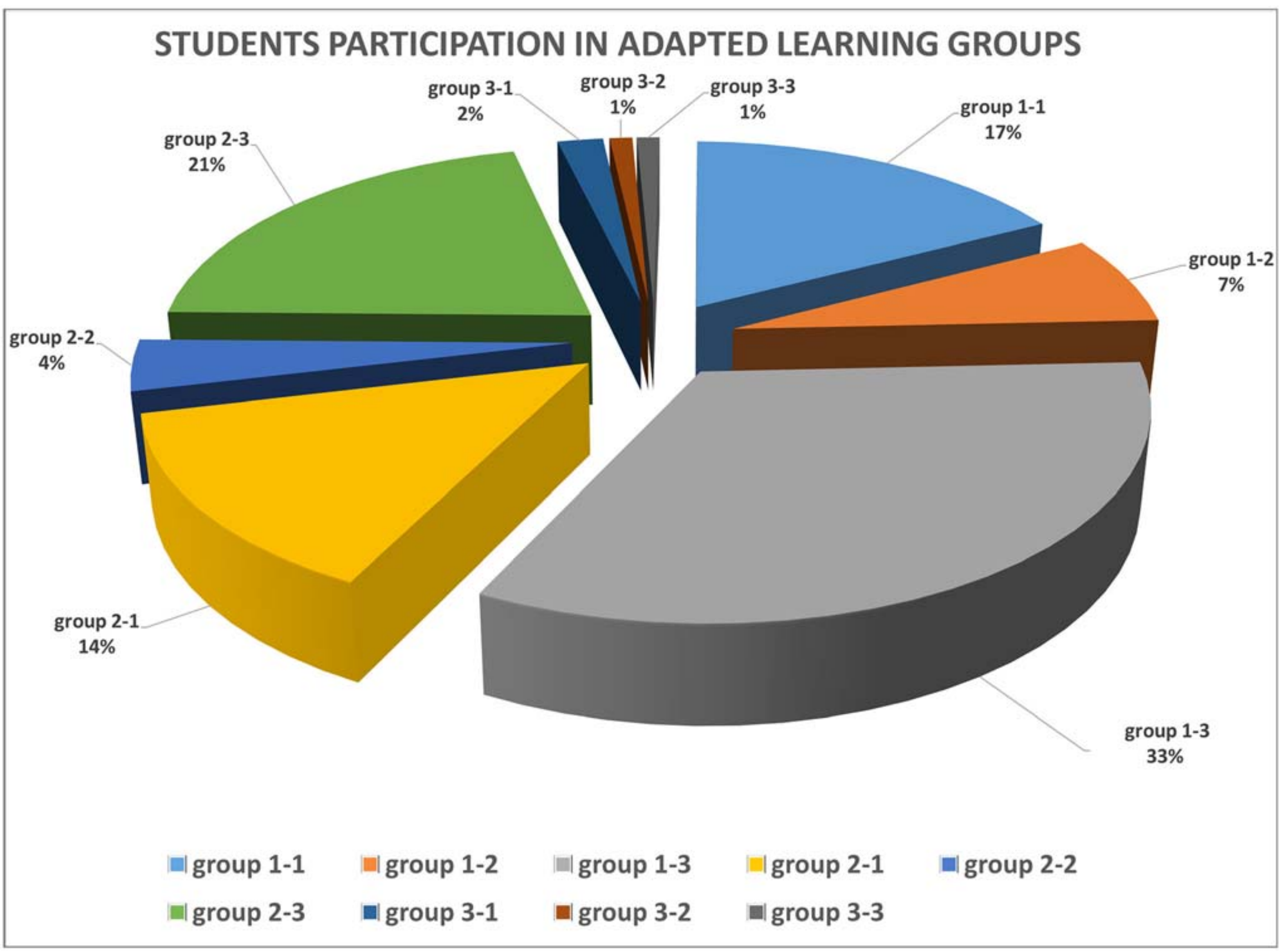

Figure 3. Students' participation in adapted learning groups.

was performed. The influence of the variables on the positive marks of students was examined by multivariate binary logistic regression. Receiver operating characteristic (ROC) curve was generated and the area under the curve (AUROC) was calculated. Sensitivity and specificity for optimal cut-off were calculated. Differences were considered significant at $p < 0.05$.

4.1 *Statistical methods*

Data collected in the conducted experiment were analysed by statistical analysis and the following results were obtained. Table 1 shows the numbers and percentages of students according to the type of course, students' previous knowledge and learning style.

Differences in the mean value of time spent on the course between the beginner, intermediate and advanced knowledge students are statistically significant ($p = 0.011$). The mean value of the time spent on the course for beginners is 41.14 ± 20.47, the mean value of the time spent on the course for students with intermediate knowledge is 38.89 ± 15.78 and the mean value of the time spent on the course for students with advanced knowledge is 17.17 ± 19.10.

Differences in the mean values of the logging number between beginner, intermediate and advanced are statistically significant ($p = 0.027$). The mean value of the logging number for beginner is 32.61 ± 20.13, the mean value of the logging number for intermediate knowledge is 28.09 ± 13.19 and the mean value of the logging number for advanced knowledge is 14.50 ± 17.83.

Difference of mean values of time spent on the course between students who attended the traditional way course and the students who attended adaptive course is statistically significant ($p = 0.002$). The difference between the mean values of the logins number of students who attended the traditional and the students who attended the adaptive course is statistically significant ($p < 0.0005$). The difference between the mean values for marks of students who attended the traditional and the students who attended the adaptive course is statistically significant ($p < 0.0005$).

Table 1. Categorical variable**s.**

Variables	Category	Number
Course type	Traditional	79 (49.4%)
	Adaptive	81 (50.6%)
Prior knowledge	Beginner	90 (56.3%)
	Intermediate (knowledge)	64 (40,0%)
	Advanced (knowledge)	6 (3.8%)
Learning style	V-S-A	54 (33.8%)
	I-A-G	19 (41.4%)
	V-A-S	87 (61.8%)

Therefore, students who have attended the traditional course, spent more time on the course, they will be logging in more times and get lower marks (see Table 2).

The difference in the mean value of marks between students who attended a traditional, non-adaptive course and students who attended the adaptive course is statistically significant ($r < 0.0005$). The intermediate mark for students who attended the traditional course is 6.39 ± 1.21, and for students in an adaptive course is 7.26 ± 1.62 (see Table 3).

Differences in the mean value for marks between the beginner, intermediate and advanced knowledge students are statistically significant ($p < 0.005$). Differences in the mean value for marks between the visual, intuitive and verbal learning style are statistically significant ($p = 0.002$). See Table 4.

Linear regression showed that mark depends on the time spent on the course ($p < 0.0005$), on the course type/adaptive course ($p < 0.0005$) and whether the student is beginner ($p < 0.0005$), wherein $R^2 = 0.562$.

Equation of regression plane is defined as:

$$Mark = 0.036 \cdot (\textit{time spent on course}) + 1.122 \cdot (\textit{adaptive course}) -1.729 \cdot \textit{Beginner} - 1.729. \quad (1)$$

So, the mark is higher if the time spent on course and the number of logging are greater, and the mark is less if student is a beginner.

There were 38 (23.8%) negative marks (failed), and positive marks (passed) were 122 (76.2%). Students who attended the traditional online course have achieved the passing rate of 70.89%, while students who attended the adaptive course have achieved higher passing rate of 88.48%.

Experience, or prior knowledge (beginner and not beginner), and a positive mark are associate ($p = 0.008$). The percentage of positive marks for a beginner is 67.8% and for the other is 87.1%.

Multivariate binary logistic regression shows that positive mark depends on the time spent on the course ($p < 0.0005$), number of logging ($p = 0.045$), from the course adaptivity/type of course ($p = 0.028$), and whether the student is beginner ($p = 0.002$). For details, see Table 5.

Odds ratio for the time spent on course is 1.137 (1.072 – 1.206). If the time spent on course increased by one hour, the chance to get a positive mark increases by 13.7%. Similarly, if the number of logins increased by one, the chance to get a passing mark is reduced by 5.9%. If a student attended an adaptive course, the chance to get a positive mark increases about three times. If the student is beginner, a chance to get a positive mark is reduced about 6 times.

Using multivariate binary logistic regression, it is possible to make a model for predicting positive marks. This new variable is determined by the formula:

Table 2. Time spent on the course, the number of logging and marks according to the type of course.

Parameter	Traditional	Adaptive	p
Time spent on course	44.02 ± 20.93	34.79 ± 15.99	0.002
Number of logins	36.49 ± 19.84	23.91 ± 13.01	< 0.0005
Marks	6.39 ± 1.21	7.26 ± 1.62	0.001

Table 3. Students marks according to the course type.

Course Type	N	Mean	Std. Deviation	Std. Error Mean
Marks				
Traditional	79	6,3924	1,21336	0,13651
Adaptive	81	7,2593	1,61847	0,17983

Table 4. Students marks according to the prior knowledge and the learning style.

	Marks	p
Prior knowledge		
Beginner	6.11 ± 0.99	< 0.0005
Intermediate	7.78 ± 1.40	
Advanced	7.70 ± 2.74	
Learning style		
V-S-A	6.91 ± 1.46	0.002
I-A-G	7.63 ± 1.50	
V-A-S	6.61 ± 1.47	

Table 5. Multivariate binary regression.

	Odds ratio	p
Time spent on course	1.137 (1.072–1.206)	< 0.0005
Numbers of logins	0.941 (0.886–0.999)	0.045
Adaptive course	3.318 (1.141–9.653)	0.028
Beginner	0.162 (0.051–0.512)	0.002

$$Model = 100 \cdot e^{sum}(1 + e^{sum}) \tag{2}$$

wherein

$$sum = 0.129 \cdot time\ spent\ on\ course - 0.061 \cdot number\ of\ logins + 1.200 \cdot Adaptive\ course - 1.820 \cdot Beginner - 1.089.$$

ROC (receiver operating characteristic) curve shows that this model is an excellent marker for the separation of positive and negative marks (AUROC = 0.881, $p < 0.0005$), as shown in figure 4.

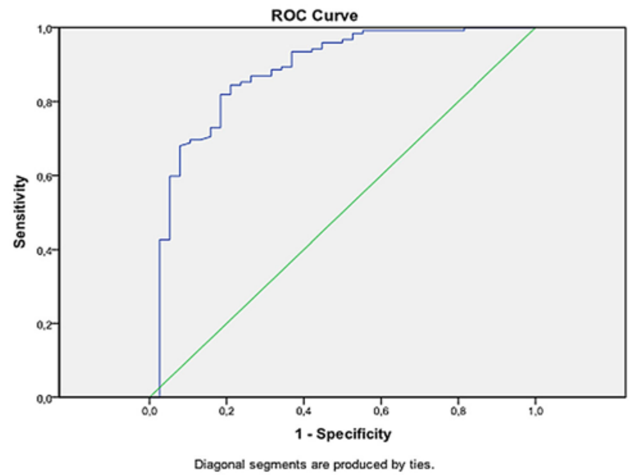

Figure 4. ROC curve.

Intersection point (cut-off) is 78. Sensitivity is 0.820, which means that of students with a positive mark, 82.0% of them have the values of the new variable (Model) greater than 78. The specificity is 0.816, which means that students with negative mark, 81.6% of them have a value of new variables (Model) less than the 78.

5. Discussion

Even though adaptivity was recognized as a promising approach for improving learning and teaching outcomes, it still has not been researched fully and in the context of LMS and electronic education. Despite the fact that many educational institutions implemented various forms of LMSs, most of them lack adaptivity features [39, 40].

The goal of this paper is to present the specific adaptive learning model, and its realization based on the widely used open-source LMS and data analytics. The adaptive learning model has been designed having in mind limitations and issues of the existing approaches, as well as the newest advancements related to personalized and adaptive learning, LMS, and data analysis.

The introduced adaptive learning model encompasses several key components, such as the Expert System, the Adaptation Module, and the Student Model, that enable a high degree of adaptivity and personalization. The model has been practically realized as an extension of the Moodle LMS platform which makes it easy to install and deploy. Taking into account both learning styles and prior knowledge, the system can provide more accurate and tailored learning experience.

The learning resource repository has been loaded with various learning objects such as lessons, topics, tasks, assignments, etc., that support adaptive learning. Based on the students' activities, choices, and achievements, the system automatically adapts course content, tests, or even teacher instructions or comments. Thanks to the SCORM compatibility, it is possible to reuse learning resources (course structure and content) in other LMSs.

The generated data through students' and teachers' activities, as well as system generated data, are used for various data analysis in order to provide valuable insights and better decision making. Teacher can monitor students' progress and performance, gain the advanced insights (hidden patterns or rules, associations, predictions, etc.), and timely and adequately act on that information. This enables more effective communication, learning, teaching, and evaluation.

The adaptive model and the accompanying software system were successfully tested in a real-world higher education environment.

All students were classified into the nine groups, categorized by learning style and additionally by prior knowledge. This system identifies the learning style and prior knowledge of students and accordingly provides compatible learning material and customizes its mode of presentation based on students' preferences. This improves the students' learning ability and the performance (grades). The adaptive model customizes and provides the materials that enhance the student's learning experience and satisfaction. In the future, the presented adaptive model and the solution will be tested for different courses and for a larger number of participants. The proposed adaptive model can enhance educational processes in terms of improving learning performance, personalized application of teaching/learning methods as well as continuous improvement cycle.

The conducted experiment showed the existence of differences in the learning achievements of students with different levels of prior knowledge (beginner, intermediate or advanced), as well as between students attending different types of courses (traditional, non-adaptive e-learning or adaptive e-learning course). Moreover, it was shown that the differences in achievement among students of different learning styles are not so large (although they are statistically significant). This is expected because the learning style is a matter of student's personal preference, rather than restricted characteristic such as the level of prior knowledge [41]. One of the studies, also based on the Moodle LMS [42], shows that combination of adaptivity (in terms of learning styles) and data mining clustering models (for students' segmentation) provide better students' performance (% of students who passes the course). The results confirm that students who attended the adaptive course have achieved higher marks, and the pass rate was also higher. Research also show that adaptive e-learning can be applied at various education levels, such as primary education [43].

Students with different levels of prior knowledge are represented in all learning styles. Therefore, most of the results are considered in terms of the correlation among students' achievement and levels of their prior knowledge, as well as the correlation among students' achievement and time spent on course, numbers of login, or course type.

Research shows that beginners and students with intermediate prior knowledge level spent more time on course, as opposed to students with an advanced level of prior knowledge. The situation is similar to the number of logins to the course, compared to students' prior knowledge level. Also, the more time spent on the course had students who have attended a traditional non-adaptive e-learning course, other than those who attended adapted e-learning course. To conclude, students who attended an adapted course, spent less time on the course, login less time, and achieved an average better grade than students who attended the traditional course.

Processed data also shows that achievement, in the form of the final mark, depends on the time spent on the course, but also on the course type (whether it is adapted), as well as on whether the student is a beginner. The outcomes are better if the number of logins and the time spent on the course (adaptive) are higher. However, the possibility of a positive outcome decreases if the student is a beginner.

6. Conclusion

Developing of the adaptive LMS is a wide research area. Adaptivity is a significant issue in LMS, but commercial learning systems that integrate adaptivity in contemporary e-education are rare and with limited adaptive capabilities. Therefore, a special challenge is the development of the LMS that enables personalization of learning, so-called adaptive LMS.

This paper presents the adaptive learning model that provide a high level of adaptivity, and flexibility to accommodate various learning and teaching scenarios. Its Expert System, Adaptation Module, and Repository of learning objects and teaching methods, enable more adjusted and personalised learning experience. Personalization of learning in two aspects (learning style and previous knowledge) represents a noteworthy shift in the approach to the creation of an adaptive LMS.

The developed adaptive learning model and the software components were tested on a real student sample and proved to be successful. The success of learning with this adaptive LMS is reflected in the ability to personalize learning according to students' preferences and better achievements and learning outcomes (which are reflected in better grades, improved students' level of knowledge, quantity, and quality of time spent in learning).

This study compared an adaptive LMS with a traditional, non-adaptive LMS. As expected, it turned out that an adaptive learning environment has a positive impact on learning achievements and learning outcomes. Analysis of the obtained data led to the conclusion that the success of learning is affected by course adaptivity, number of logins, time spent on the course and prior knowledge (whether the student is a beginner or not). It was shown that the best results were achieved by the students who attended an adaptive course, had an optimal duration of login sessions, better efficiency of activity realization, and those which had some prior knowledge. These results and outcomes justify the improvement of LMS in terms of adaptivity because in this way the effectiveness of learning and learning outcomes are improved.

The developed model for LMS adaptivity and the developed software application proved to be useful in enhancing learning processes and learning outcomes of the students. Based on the conducted data analysis, valuable information and knowledge have been obtained that can be used for better decision making and improvement of the teaching and learning strategy. The results obtained will be used as a guideline for further research in improving adaptive LMS development and design, as well as for improving the software expert system for more insightful decision making.

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