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A MODEL OF ADAPTIVE LEARNING IN SMART CLASSROOMS BASED ON THE LEARNING STRATEGIES

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Abstract

The paper presents a proposal of a model of adaptive learning. The model takes the advantage of a smart classroom environment for the realization of adaptive learning. As adaptation criteria, it uses parameters of motivation, student's prior knowledge, cognitive load and a dynamic environmental parameter. The dynamic environmental parameter is a parameter which is obtained by evaluating physical parameters of working environment in a smart classroom. The learning process is carried out through different learning strategies grouped in learning categories. The model dedicates a learning category to a student based on a formula which takes in consideration above mentioned adaptation criteria The proposed model has been tested. The assessment test scores at the end of a learning process showed that student's in the experimental group achieved better learning outcomes than the student's who learned in a traditional manner. The obtained *results are encouraging and lay a sound foundation for the application and further development of the model.*

Keywords
Adaptive Learning; Dynamic Environmental Parameter; Learning Environment; Personalization Parameters; Smart Classroom

1. Introduction

The learning success depends not only on cognitive processes incorporated in learning but on some other factors as well, such as motivation, physical characteristics of working environment, student's prior knowledge, student's learning style, etc. Working environment should be created to encourage a student to learn. Well-equipped working environments wherein a student can accomplish his or her learning objectives have positive impact on learning (Mekacher, 2019).

This paper presents a model of adaptive learning in smart classrooms which uses parameters of motivation, student's prior knowledge, cognitive load as well as physical environmental parameters as the parameters of adaptive learning in smart classrooms. The model aims at taking the full advantage of smart learning environments which enable continual monitoring of physical environmental parameters, thus providing the possibilities for the realization and evaluation of the adaptive learning model in real time. Besides the review of fields of science relevant for the establishment of the model, the paper also presents the results of the research the ultimate aim of which was to justify the concept of adapting learning process in smart classrooms by assigning learning categories to a student. The drawn conclusions have confirmed that the model has positive effect on the learning outcome.

2. Literature Review

2.1 Adaptive Learning

Adaptive learning is defined as a dynamic learning process allowing students to opt for a learning style in pursuit of successful academic outcomes (Beldagli and Adiguzel, 2010) (Pace, 2017). Smart classroom environment offers a wide range of possibilities for adaptive educational process and the personalization of learning. Research questions raised in this field focus on the choice of the characteristics that should be considered in the process of adaptive learning and the potential of its implementation, as well as the personalization of educational process. The student is most commonly analyzed from three aspects: personal characteristics, prior knowledge and cognitive characteristics. The student's attitude towards learning is described through personal characteristics, while prior knowledge defines the student's knowledge level at the beginning of a learning process. Cognitive characteristics refer to the student's abilities to process data (Kim et al., 2013).

2.2 Motivation in Learning

Motivation is a factor which stimulates the activities of an individual: initiates and maintains a certain behavior, directing it towards a certain goal. The research of student's motivation based on achievement-goal theory (Pintrich, 2000), self-determination theory (Gagnie and Deci, 2005) (Ryan and Deci, 2017) and social-cognitive theory (Schunk, 1989) has shown that in the classroom student's motivation has directly been related to the way student's perceive their success. To acquire successful outcomes, a classroom should be such an environment which would encourage a student to carry out the assignments successfully and efficiently, individually yet to provide the feeling of cooperation with other student's. Learning environment which supports the development of student's skills and enables them to successfully realize their assignments has a positive effect on motivation. According to the ARCS motivation model, in case a student is insufficiently motivated or primarily expresses extrinsic motivation, it is necessary to increase certain motivation elements, namely student's attention, relevance, confidence and satisfaction (Chang et al., 2016).

2.3 Cognitive Load

In technologically-supported learning environments (e.g. e-learning platforms or smart classrooms) it is necessary to correlate learning materials with student's cognitive load. Due to the smaller degree of immediate communication with the teacher, learning materials and environment should help create adequate mental knowledge models (Boekaerts, 2017). To achieve best learning outcomes, students must integrate all types of cognitive load into a unique entity which will provide them with complete mental projection of information to be processed and acquired. These cognitive loads include information content, content structure and engagement as a response to received information (Miller, 1956). Technology-supported learning environments (e.g. smart classrooms and e-learning platforms) should bring about the decrease of irrelevant data in the learning process and the creation of adequate mental knowledge models. The application of applying suitable multimedia material and learning strategies can affect a student's cognitive load in the learning process and create adequate mental learning models (Kassim, 2013).

2.4 Physical Environmental Parameters

The physical arrangement of the classroom can affect the behaviors of both student's and teachers and can improve student's academic outcomes (Yang and Huang, 2015). The optimum temperature values of the working environments are between 20°C and 24°C in some researches, subjective evaluation of thermal comfort has been used for the description of desired temperature features of working environment (Ricciardi and Buratti, 2018). Air quality refers to the existence of certain gases or chemical compounds, the quantity of carbon-dioxide in the air, as well as the frequency of room ventilation. The research has shown that inadequate ventilation and high concentration of carbon-dioxide in the classroom decrease student's attention, their learning performances, as well as the speed of data processing and carrying out assignments (Wald and Howard, 1975). Lighting has influence on student's physical and mental states (Wurtman, 1975). Research has pointed out that learning in a well lit room correlated with the acquisition of good learning outcomes. Student's learning in a well-lit classroom show better results compared to student's learning in an insufficiently lit classroom. (Ricciardi and Buratti, 2018). Noise affects student's performance. Student's learning abilities decrease due to noise. Loud noise brings about frequent disruption of learning process, thus reducing time efficiency of learning process. The noise made by two people talking in a classroom disturbs student's more than any ambient noise (Crook and Langdon, 1974).

3. Adaptive Learning Model in a Smart Classroom

The adaptive learning model in a smart classroom environment as put forward in this paper is composed of three segments:

- a student,
- smart educational system
- a teacher (Figure 1).

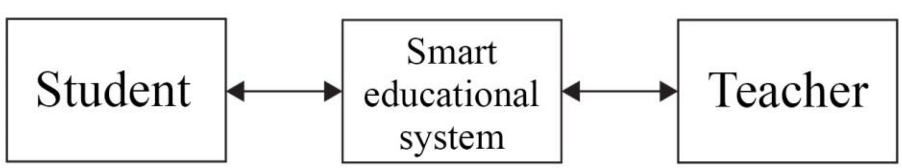

Figure 1: *Basic Block Diagram of the Model*

In the model, students are presented through their profiles. Student's profiles are defined by their personal data, examination details, skills, experience with e-learning platforms, etc. Student's profiles assist in determining individual personalization parameters used in the adaptive learning model.

Smart educational system represents a part of a system which monitors the adaptation process of teaching, controls multimedia contents used as learning materials, intermediates in communication among student's, between student's and teachers, as well as between a smart system and other (external) systems.

The teacher controls and monitors the model through the smart educational system. The teacher provides instructions and guidance to student's during the whole learning process, constantly monitoring the quality of learning materials and the process of adaptive learning in a smart classroom.

The model of adaptive learning in smart classrooms offers the possibility for automated individual adaptation of a learning process. Learning adaptation is realized on the basis of both individual and global personalization parameters (Table 1).

Table 1: *Description of Model Parameters*

Parameter	**Value**
(M)	Motivation parameter M describes a student's current level of motivation and can have values in the ratio from 0 to 1. The value 0 refers to the absence of student's intrinsic motivation for learning in the field being studied. The value 1 represents student's maximum intrinsic motivation for learning.
(P)	Parameter P Describes a student's prior knowledge in the field being studied. It can have values in the ratio from 0 to 1. The value 0 refers to the total absence of prior knowledge in the field being studied, while the value 1 represents high level of prior knowledge.
(C)	Parameter C Describes a student's expected cognitive load in the field being studied. It can have values in the ratio from 0 to 1. The value 0 refers to the minimum cognitive load. The value 1 represents student's maximum mental engagement.

(λ)	Minimum value, (λ =0), is used to describe smart classroom environment which is highly favorable for learning and work. Maximum value of dynamic environmental parameter (λ =1) describes smart classroom environment as highly unfavorable for learning and work.

The model adapts a learning process by assigning a learning category to a student. Each learning category provides a student with certain learning strategies that requires specific engagement of a student in the process of learning. Learning category is a set of learning strategies assigned to each student according to his/her individual and global personalization parameters, which is calculated by applying the following formula:

$$K = (1 - \lambda)M + P + \lambda(1 - C)$$

The model classifies learning strategies in 5 categories. In accordance with the defined value ratio of parameters, maximum value of a category is K=2, and minimum is K=0. The given number of categories is determined on the basis of the research (Lee and Paek, 2014) stating that the optimum number of categories in psychometric measurements ranges from 4 to 6, which is highly dependent on the field of study, level of education, the feasibility of implementation in a smart classroom, etc. According to the model, every category has a limited number of learning strategies.

The wide variety of learning strategies provides students with the possibility to find their optimum combination of learning styles aimed at better learning outcomes. Learning strategies are assigned to the corresponding learning categories due to the amount and the type of engagement expected from a student. Choosing the appropriate learning strategy positively influences the student’s cognitive engagement and inner motivation, which defines a set of learning strategies offered within categories.

Based on given personalization parameters, a student is offered only those strategies which are optimum for him/her. According to the model, a student learns using the first strategy within the assigned category. In case the desired learning outcomes are not achieved, a student is assigned the next strategy within the same category. Student’s are allowed to change their categories to a lower level. An example of the distribution of learning strategies in categories can be seen in Table 2.

Table 2: *Learning Categories with Learning Strategies as Presented by the Model*

Category	Learning style 1	Learning style 2	Learning style 3	Learning style 4	Learning style 5	F2F with the teacher	Possibility of change
K=2	+	-	-	-	-	+	to lower level
K=1.5	+	+	-	-	-	+	to lower level
K=1	-	+	+	-	-	+	to lower level
K=0.5	-	-	+	+	-	+	to lower level
K=0	-	-	-	+	+	+	to lower level

Some learning strategies that can be offered in learning categories are Felders-Silverman ILS model - One of the most frequently used models for determining learning, problem-solving simulation, peer-to-peer discussion, essay writing and sharing, collaboration with the teacher.

Although smart classroom system manages and monitors student's learning, students are actively engaged in the process of their knowledge development. The model supports social interaction among the participants in the learning system. Smart classroom environment should equip student's with necessary tools to meet the requirements. Through smart classroom services students are supplied with the adequate learning material and enabled to employ the most suitable learning strategies to complete the tasks. The whole process has been regulated and evaluated on the basis of accomplished assignments.

4. Research

In order to assess the proposed model, the research wad performed at the ICT College of Vocational Studies in Belgrade (Serbia) in May 2018. The research implemented an experiment which was carried out in a classroom where physical environmental parameters could be monitored and controlled (air temperature, lighting, air ventilation and noise). An overall of 80 third year students participated in the experiment. Student's were divided into two groups, the experimental group and the control group. The insignificant statistical deviation between these two groups was gained by grouping student's only by their index numbers (a unique identification number each student is given upon admission to school). All student's attended lab drill sessions as part of the course of Digital telecommunications.

The experiment was aimed at confirming that student's who were assigned the adequate learning categories determined by the model acquire better learning outcomes at the final assessment test as compared to student's who learned in the traditional learning manner.

According to the model, the personalization parameters used in the adaptation process are motivation (M), pre-knowledge (P), cognitive load (C) and dynamic environmental parameter (λ). Learning category with defined learning strategies is calculated according to the formula $K=(1-\lambda) +P + \lambda(1-C)$. Learning strategies are organized into categories according to the level of student's' engagement within the strategy (Table 3).

During the experiment, the dynamic environmental parameter (λ) was maintained at the constant value of $\lambda=0$. Environmental parameters were maintained at the optimum level (air temperature of 23° C, adequate lighting (Blog (2016)), proper ventilation (www.hydroponics.eu (2016)), noise level below 45 dB). Cognitive load parameter was set by the teacher. Motivation and pre-knowledge parameters had discrete values of 0, 0.5 and 1, (Table 4 and Table 5). The discrete values of the parameter (M) and (P) are defined so that all the data range of the parameters are equally probable.

Table 3: *Distribution of Learning Strategies in Categories used in Experiment*

Category	**Learning style 1 Felder-Silverman ILS model**	**Learning style 2 Problem-solving simulation**	**Learning style 3 Peer-to-peer discussion**	**F2F with the teacher**	**Possibility of change**
K=2	+	-	-	+	to lower level
K=1.5	-	+	-	+	to lower level
K=1	-	-	+	+	to lower level
K=0.5	-	-	-	+	to lower level
K=0	-	-	-	+	to lower level

Based on the values of the personalization parameters, formula for learning category calculation and distribution learning strategies in categories (Table 3), Table 6 was formed.

Table 4: *Scores of Pre-Knowledge (P) Parameter*

Student's scores at prior knowledge assessment test (%)	Pre-knowledge parameter (P)
(0-33)	0
(33-66)	0.5
(66-100)	1

Table 5: *Scores of Pre-Knowledge (P) Parameter*

Mean scores of student's motivation based on motivation questionnaire (scale 1-7)	Motivation parameter (M)
(0-2.33)	0
(2.33-4.66)	0.5
(4.66-7)	1

Table 6: *Learning Strategies Applied in the Experiment*

M (motivation)	P (prior knowledge)	C (cognitive load)	λ (dynamic environmental parameter)	К (category of learning strategy) К=(1-λ)M+P+ λ(1-C)	Learning strategy
0	0	0/0.5/1	0	0	F2F collaboration with the teacher
0	0.5	0/0.5/1	0	0.5	F2F collaboration with the teacher
0	1	0/0.5/1	0	1	Peer-to-peer discussion
0.5	0	0/0.5/1	0	0.5	F2F collaboration with the teacher
0.5	0.5	0/0.5/1	0	1	Peer-to-peer discussion
0.5	1	0/0.5/1	0	1.5	Problem-solving simulation
1	0	0/0.5/1	0	1	Peer-to-peer discussion
1	0.5	0/0.5/1	0	1.5	Problem-solving simulation

1	1	0/0.5/1	0	2	Felder-Silverman ILS model of learning styles

Student's who formed control group (total of 40 student's) participated in the learning process in the traditional manner. The lesson started with the introductory lecture. The introductory lecture was delivered by the teacher. It specified the content and goals of a lesson unit. In the introductory lecture, the terms and the field to be studied in the lesson were defined. At the end of introductory lesson, students filled in the questionnaire aimed at defining their motivation level based on ARCS motivation model at the given moment. Afterwards, students did a test to assess their prior knowledge in the field being studied. The teacher then held the lectures, by giving oral presentations of learning material and performing follow-up simulations with additional explanations. At the end of the class, students did the assessment test. The lectures were held in favourable physical environment. Student's who formed experimental group (total of 40 student's) participated in the learning process by following an instructional plan. The students came to the lecture and initially signed into a user account on the smart educational system. Through the system, the teacher distributed e-learning materials supporting respective learning strategies. When students were signed in, the lesson started with the introductory lecture. The introductory lecture was delivered by the teacher. It specified the content and goals of a lesson unit. In the introductory lecture, the terms and the field to be studied in the lesson were defined. At the end of introductory lesson, students filled in the questionnaire aimed at defining student's motivation level at the given moment, i.e. the value of parameter (M). The questionnaire was based on ARCS motivation model created according to the research of learner motivation level (Huang and Hew, 2016). ARCS model refers to measurements of motivation aspects through attention, relevance, confidence and satisfaction. Student then took the entry test evaluating their prior knowledge, as a prerequisite for the lecture. Test scores defined parameter (P). The teacher defined parameter of expected cognitive load (C). Environmental parameters were considered by the system in order to define dynamic environmental parameter λ. The defined parameters were used to calculate a learning category to be assigned to each student. The assigned learning category gave each student a category with pre-defined learning strategies. Student's learned the instructional material by applying adequate learning strategies. At any moment during the learning process, the student could ask the teacher for help and advice. When students acquired the complete learning material planned by the syllabus or when the lesson time elapsed student's did the assessment test.

4.1 Experiment Results

Experiment results are classified into three groups: motivation, prior knowledge and final test achievement.

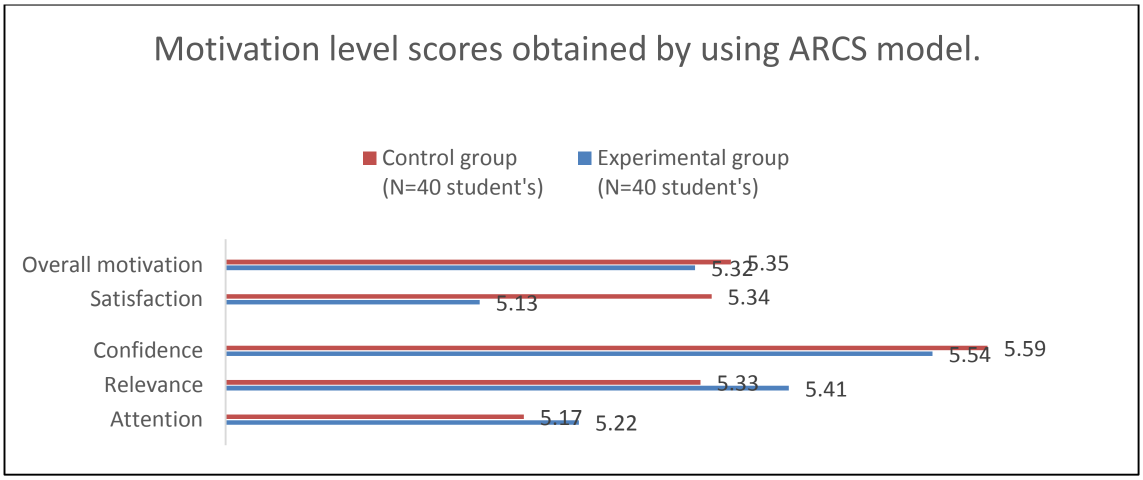

Figure 2: *Motivation Level Scores Obtained by using ARCS Model*

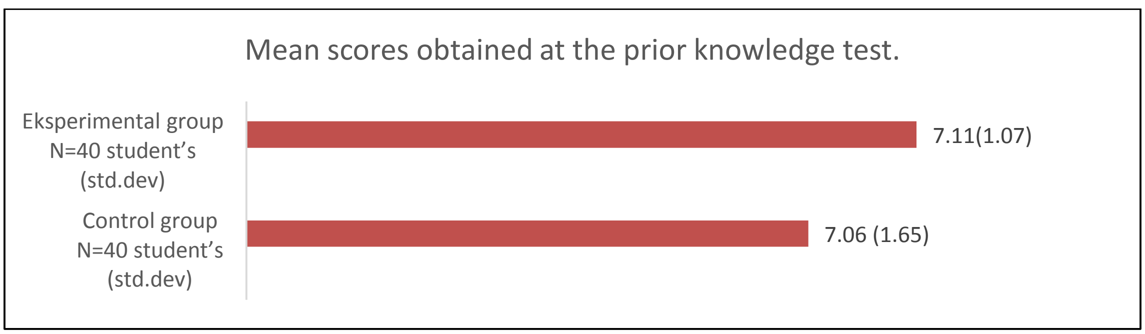

Figure 3: *Mean Scores Obtained at the Prior Knowledge Test*

On the basis of prior knowledge test scores and motivation level questionnaire the values of prior knowledge (P) and motivation (M) parameters for experimental group were calculated. Figure 4 shows the number of student's for each parameter value.

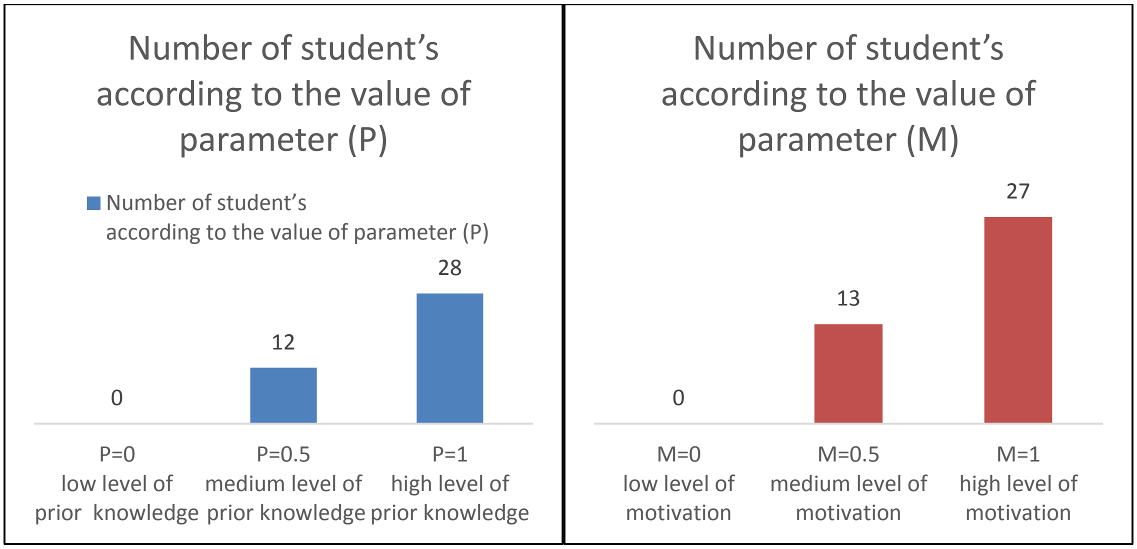

Figure 4: *Number of student's according to the assigned values of prior knowledge (P) and motivation (M) parameters (N=40)*

Figure 5 shows learning category values calculated according to the assigned parameters (M),(P),(C) and (λ). Parameter (C) did not have any influence on the calculation of categories since in case of optimum physical environment parameter (λ=0), in formula (K=(1-λ) +P + λ(1-C)), cognitive load influence is irrelevant.

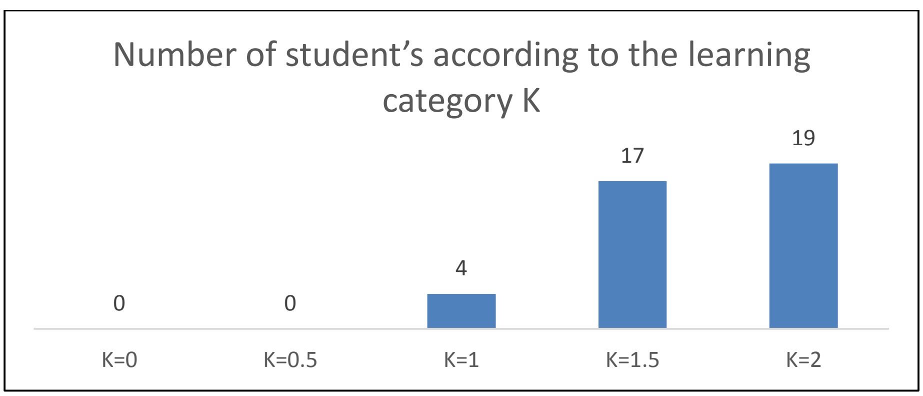

Figure 5: *Number of student's in learning categories (N=40)*

Assessment tests student's of both control and experimental groups took at the end of the class showed that student's in experimental group achieved better test scores than student's in control group. Mean assessment test score in control group was 7.23, while mean assessment test scoe in experimental group was 8.09, as shown in Figure 6. The results of applied t-test showed significance value of 0.04 ($p < 0.05$), thus rejecting zero hypothesis. By conventional criteria, this difference is considered to be statistically significant. Therefore, mean assessment test values were confirmed to be statistically different. Online t-test calculator was used for calculation (Motulsky, 2018).

5. Discussion

The model presented in this paper has resulted from the research in the field of adaptive learning in smart classroom environments (Mihalca et al., 2011) (Brusilovsky and Peylo, 2003) (Essalmi et al., 2015). The process of personalization, i.e. the adaptation of a learning system to student's needs, can be analyzed through the model from three aspects.

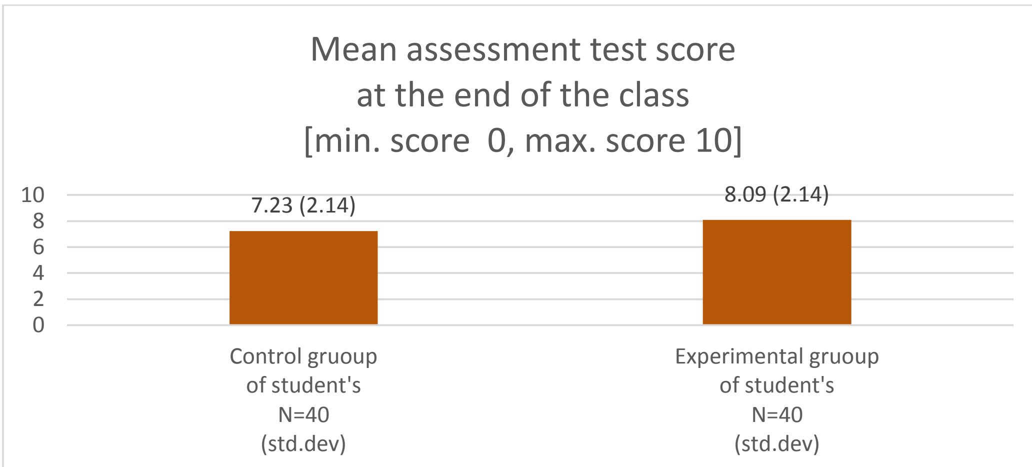

Figure 6: *Mean Assessment Test Score at the End of the Class*

The first aspect refers to the design of a student-centered system. An effective learning process is provided through the learning categories assigned to the student and the strategies within the categories available to the student. A smart classroom and the model realize the adaptation of a learning process according to the physical parameters of student's learning environment as well as student's individual parameters such as motivation, prior knowledge and predicted cognitive load. The smart educational system along with the teacher provide support to student's in the learning process. The effectiveness of learning by selecting appropriate learning strategies has been confirmed through success students achieve at the final test. Having observed final test scores as well as work conditions in the experiment, the implemented model has been proved effective.

The second aspect of model analysis refers to the assignment of learning categories with adequate strategies according to individual and global personalization parameters. The number of learning strategies within learning categories should be appropriate to both student's and their learning environment. The optimum number of learning strategies offered to student's within different learning categories also requires additional research. In this phase of model development, learning strategies have been assigned to learning categories on the basis of some research results as well as due to the extensive experience the authors of this paper have had in teaching.

The third aspect refers to the adaptation of a learning process, i.e. the selection of personalization parameters. The selection of individual personalization parameters is based on the research (Essalmi et al., 2015) in which 19 possible personalization parameters classified into three groups were analyzed. The first group of parameters refers to motivation and provides the answer to the following question: ’Why should I learn?’. The second group of parameters takes into consideration student’s prior knowledge and defines information and knowledge students should acquire. These parameters provide the answer to the question: ’What should I learn?’. The third group of parameters refers to the application of different learning strategies and provides the answer to the question: ’How should I learn?’. The model presented in this paper combines personalization parameters from all three groups, plus a global parameter λ which describes physical parameters of student’s learning environment. Smart educational system enables both the calculation of parameter λ, and the integration of all four above-mentioned parameters in the process of learning personalization.

6. Conclusion

The model of adaptive learning presented in this paper takes the advantage of a smart classroom environment for the realization of adaptive learning. It was developed in order to organize learning strategies into learning categories using personalization parameters, resulting in positive influence on the process of learning in a smart classroom. The model of adaptive learning presented takes the advantage of a smart classroom environment for the realization of adaptive learning. Learning categories the model assigns to student’s enable them to apply individual approach to learning materials aiming at efficient and effective learning. The assessment test scores at the end of a learning process showed that student’s in the experimental group achieved better learning outcomes than the student’s who learned in a traditional manner. The obtained results are encouraging and lay a sound foundation for the application and further development of the model.

6.1 Research Limitations

The shortcoming of the implemented model has centered on the feasibility of its realization. The model is complex for the realization and requires considerable initial engagement of participants, especially from teachers during the preparation of learning materials. Each learning strategy should be assigned the appropriate learning material covering the same field being studied.

The second shortcoming regarding the realization of the model refers to the availability of a smart classroom environment. Smart classrooms well-equipped with sensors for measuring various physical environmental parameters are not so common. The model requires investment into the equipment of a smart classroom and the design of an adequate sensor network and a system for monitoring and controlling physical environmental parameters in the classroom.

6.2 Future Research

Nevertheless, besides above-mentioned shortcomings, this model provides strong grounds for further investigation. Future research should study the effects of various learning strategies which might be implemented in the model as well as the application of a number of different learning categories and adequate strategies, but without losing the quality in the process of adaptation. Furthermore, one of the research objectives should be the creation of a more precise method of selecting learning categories according to the relevant parameters.

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