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The Effects and Effectiveness of An Adaptive E-Learning System on The Learning Process and Performance of Students

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Abstract: Students acquire learning material in different ways. Some prefer to read, some prefer to listen, others use the third type of sense. Traditional teaching uses only one of these teaching strategies since it is impossible to use all of them in the classroom. However, these days, adaptive e-learning systems enable learning material to be customized to the individual needs of learners. For the purpose of this paper, the researchers designed a model of the adaptive learning management system and implemented it in Moodle. The system was evaluated on 228 students. The incorporation of learning styles in Moodle is based on the VAK learning style model. The authors analysed the effects and effectiveness of an adaptive e-learning system. It was discovered that there are significant differences in learning effectiveness, satisfaction and motivation when students use an adaptive e-learning module in comparison to a standard e-learning module. Moreover, we investigated the durability of knowledge acquired with an adaptive e-learning system by comparing the performance of students not only after the completion of the course but also a month after the course. The results of the research confirmed the authors' expectations and showed that an adaptive e-learning system can increase students' learning results. So far, to our knowledge, no study has evaluated the performance between a control and experiment group a few months after the completion of the course, i.e. by analysing the durability of knowledge acquired through an adaptive e-learning system. Moreover, the motivation of students to continue using an adaptive e-learning system hasn't been analysed until now.

Keywords: adaptive learning system; e-learning; learning style; Moodle.

Introduction

Globalisation, new social trends, and cutting-edge technology have introduced changes in the labour market which have led to changes in the education system. New education concepts combined with cutting-edge technology put an emphasis on learners' autonomy and adaptation of education to learners' needs. The electronic learning systems have been tailored to enhance effective learning and material retention. Moreover, their objectives and content can be changed depending on the individual preferences of students (Cakir, Teker and Can Aybek, 2015).

Students acquire learning materials in different ways. Some of them prefer to read, some prefer to listen, others use the third type of sense (Tamura, Yamamuro and Okamoto, 2006). Traditional teaching tends to use only one of these three teaching strategies since it is impossible to use all of them in the classroom (Kanaksabee, Odit and Ramdoyal, 2011). Rukanuddin, Hafiz and Asfia (2016) pointed out that individual students' preferences influence their learning achievements and performance. Smith-Jentsch et al. (1996) and Ford and Chen (2000) have emphasized that we have to consider students' prior knowledge, experience, background, and learning styles to achieve high learning performance. Nowadays, adaptive e-learning systems enable learning material to be customized to the individual needs of learners.

A learning style is defined as the way a student responds to a teacher's stimulus (Zulfiani, Suwarna and Miranto, 2018). Over the last thirty years, more than seventy different learning style models and theories have been developed that emphasize that students prefer to learn in a different way (Coffield et al., 2004). Some of the most famous learning style models and frequently applied in adaptive e-learning

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systems include: the Fedler-Silverman Index of Learning Styles, the Honey and Munford Model, the Kolb model, the Dunn and Dunn's Model and the VAK/VARK model (Truong, 2016).

After reviewing the current literature, we have identified that adaptive e-learning systems have used different targets for learning styles' adaptation, and some of them have used even more than one target. That majority of authors have adapted learning contents and resources by trying to identify those that would be suitable for users' learning styles (Alkhuraijietal, Cheetham and Bamasak, 2011; Baldiris et al., 2008; Brown, 2007; Cabada et al., 2009; Del Corso, Ovcin and Morrone, 2005; Dwivedi and Bharadwaj, 2013; Germanakos et al, 2008; García, Schiaffino and Amandi, 2008; Graf, 2007; Graf, Kinshuk and Liu, 2009; Jovanović, Gašević and Devedžić, 2009; Jovanović, Gašević and Devedžić, 2009; Limongelli et al., 2009; Özyurt, Özyurt and Baki, 2013; Popescu, Badica and Moraret, 2010; Sancho, Martínez and Fernández-Manjón, 2005; Sevarac, Devedzic and Jovanovic, 2012; Siadaty and Taghiyareh, 2007; Sterbini and Temperini, 2009; Sun, Joy and Griffiths, 2007; Yang, Hwang and Yang, 2013). Others have developed personalised tutorials, recommendations and teaching strategies that are adapted according to individual learning styles (Baldiris et al., 2008; Cabada et al., 2009; El Bachari, Abelwahed and El Adnani, 2011; Franzoni et al., 2008; Kelly and Tangney, 2005; Latham, Crockett and McLean, 2014; Latham et al., 2012; Schiaffino, Garcia and Amandi, 2008; Mustafa and Sharif, 2011; Wang, Wang and Huang, 2008). Some authors focused on adapting the assessment and reviewing process to students' learning styles (Baldiris et al., 2008; Cabada, Estrada and García, 2011; Wen et al., 2007). For example, Wen et al. (2007) tried to improve peer assessment by applying learning styles and, thus, decreasing bias. Lin et al. (2013) and Feldman, Monteserin and Amandi (2014) found out that the level of students' creativity can be improved if their learning styles were considered when educational games were developed. Moreover, learning style can be gleaned from the behaviour of students when they play educational games (Feldman, Monteserin and Amandi , 2014).

So far, only some studies have tested the adaptive e-learning system and conducted the evaluation. Generally speaking, most of the results of the evaluation have been positive. The majority of authors used satisfaction questionnaires which have shown that students are satisfied with the system, its usability, helpfulness , usefulness and handiness (Cabada, Estrada and García, 2011; Jovanović, Gašević and Devedžić, 2009; Limongelli et al., 2009; Limongelli et al., 2011; Özyurt, Özyurt and Baki, 2013; Sevarac, Devedzic and Jovanovic, 2012; Mustafa and Sharif, 2011; Latham et al., 2012; Schiaffino, Garcia and Amandi, 2008; Wang, Wang and Huang, 2008). Some of these authors not only evaluated students' opinion but also evaluated teachers' opinion about the system (Limongelli et al., 2009; Limongelli et al., 2011; Sevarac, Devedzic and Jovanovic, 2012; Wang, Wang and Huang, 2008). Several studies used other methods for system evaluation. For example, a few authors evaluated pre-performance and post-performance of both control and experimental groups, with some comparing the performance of a group whose learning styles matched learning material with a group who didn't match (Sangineto et al., 2008; Siadaty and Taghiyareh, 2007; El Bachari, Abelwahed and El Adnani, 2011; Latham, Crockett and McLean, 2014). The others analysed the time needed to complete the task and browse the material, the level of task completeness and the level of engagement between control and experiment group (Yang, Hwang and Yang, 2013). Finally, there are few studies that used the combination of some or all of these methods (Bajraktarevic, Hall and Fullick, 2003; Brown, 2007; Graf, 2007; Graf, Kinshuk and Liu, 2009; Klašnja-Milićević et al., 2011; Popescu, Badica and Moraret, 2010; Tseng et al., 2008). So far, none of the studies have evaluated the performance between a control and experiment group a few months after the completion of the course, i.e. they haven't analysed the durability of the knowledge acquired through an adaptive e-learning system. Moreover, the motivation of students to continue using an adaptive e-learning system hasn't been analysed so far.

For the purpose of this paper, the researchers have designed a model of the adaptive learning management system (LMS) and implemented it in Moodle. The system was evaluated on 228 students.

Based on the analysed literature we have proposed the following hypotheses for our research:

H1: The adaptive e-learning model, while providing a higher degree of knowledge, more positively influences the knowledge duration than a standard non-adaptive e-learning system;

H2: The adaptive e-learning model increases students` learning motivation compared to a standard non-adaptive e-learning system;

H3: There is a statistically significant relationship between learning styles and achievement scores on A1, A2 and S1, S2 tests;

H4: There is a statistically significant difference between gender, learning motivation, achievement scores on tests and satisfaction with the adaptive e-learning system.

Materials and Methods

Model Design

The incorporation of learning styles in Moodle is based on the VAK learning style model (Fleming and Mills, 1992). The VAK learning model is a sensory model and is an extension of Neuro-linguistic programming models. People usually prefer a learning style that corresponds to one of the three senses, i.e. visual, auditory and kinaesthetic. People who prefer visual learning style learn by seeing things and images. People with auditory learning style learn through hearing and listening, and people with kinaesthetic learning style learn through doing something, through physical activity.

LMSs do not provide adaptivity since their main purpose is technology-enhancing learning. This model enables Moodle, as one of LMSs, to be adaptive; and material is automatically generated to suit students' learning style. Moodle learning objects in the model include: content, various multimedia objects, examples, exercises, self-assessment tests, chats, and forums. Every course that uses the model needs to consist of chapters. Chapters can be divided into learning units and one or more learning objects are included within learning units (e.g. content, examples, multimedia objects, test, etc.). The developed model is independent of Moodle and it can be integrated into every LMSs. The model is very simple, and teachers find it very user-friendly. The added elements are developed in PHP for Moodle. In Figure 1, we have presented the elements that are added to Moodle to make adaptive courses.

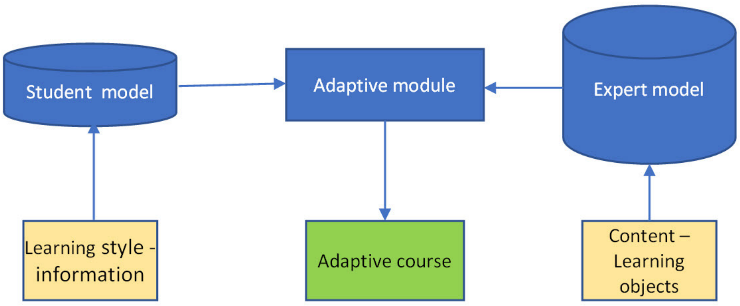

Figure 1. The implemented architecture of the LMS for providing adaptive courses

The purpose of the first element, which is based on the VAK learning style model (Fleming and Mills, 1992), is to identify and store students' learning styles. The VAK learning style questionnaire is incorporated into a student's registration form. After students complete the questionnaire, the preferences for certain learning style is identified for each student and the information is stored in the students' model.

The second element is referred to as the expert model where all available learning objects are deposited. Teachers are able to choose learning objects that will be adapted according to students' learning styles. At this stage, they can also choose objects that will not be adapted.

The third element, the adaptation module, creates courses that suit students' learning styles. The purpose of this module is to generate and provide students with courses that are adapted according to their learning styles.

A type and number of learning objects depend on the students' learning styles. For instance, students with an auditory learning style would have a higher number of audio or video material, expert narration recordings, etc. On the other hand, students with a visual learning style would be given more presentations, graphics, flow charts, text files, etc., while students with a kinaesthetic learning style would have a higher number of case studies, online video lessons, workshops, etc. Table 1 shows learning objects, assessment types and the ways of communication that are the most suitable for visual, auditory and kinaesthetic learning styles.

Table 1
Learning models and objects for VAK learning styles

Learning Styles	Visual	Auditory	Kinaesthetic
Learning Objects	Presentations Textual online lessons Diagrams, graphics, flow chart	Video materials Audio materials Homework /group activities	Case studies Online video lessons Problem based lessons Workshops Simulations
Assessment	Tests Essays Demonstrating a process	Oral exams Presentations Tests (e.g. fill in gaps)	Tests (e.g. multiple-choice questions, short definitions fill in the blanks) Research Demonstrate a principle Problem solving exercises
Communication	E-mails Forums Chats	One to one communication Video conference	Forums Discussion

The adaptive courses enable students to move to another module when they complete one and students are grouped according to their level of knowledge and successfulness in a course. The questions are created on the bases of individual abilities of students and are adjusted during an assessment. For example, when students answer one question correctly the next one will be more difficult, and if they answer the question incorrectly, the next one will be easier. The students who are better prepared for the exam will have more difficult questions and the other way around. The more difficult questions will carry more points than the less difficult ones.

Sample

We conducted research on the Faculty of Management in Serbia from September 2015 till June 2018. The sample consisted of 228 students. The demographic characteristics of the sample are shown in Table 2. The students attended the third-year undergraduate course Internet Technologies. The research included one group of students. The first half of the semester students attended a standard course, a non-adaptive e-learning course. The second half of the semester students were taught material that matched their learning styles, i.e. they attended an adaptive e-learning course.

Table 2
The demographic characteristics of the sample

	Number	Percent
Gender		
Female	92	40.4
Male	136	59.6
Age		
20-22	182	79.8
23-25	29	12.7
26-28	17	7.5
Total	228	100

The whole course was online and adjusted in Moodle. The course consisted of a practical and theoretical part. The course included 12 chapters. In the first 6 chapters students were taught via standard, non-adaptive Moodle. In the other 6 chapters, students were taught via Moodle which was extended by the adaptive concept described above.

Study Procedure

After finishing the first 6 chapters via the standard e-learning course, students completed the test (referred to as the Standard test 1- S1). Before starting the other 6 chapters, students filled out the VAK learning style questionnaire in Moodle. Once they logged into the course, it was automatically adapted to their learning style. After finishing the rest of the chapters, students finalized the test that was also adapted to their learning styles (referred as the Adaptive test 1- A1). In addition to having completed the test, students also filled out motivation and satisfaction questionnaires. One month after completion of the course, students finalized again two tests for all 12 chapters. We refer to the other two tests as the Standard test 2- S2 and Adaptive test 2- A2.

The dependent variables in this study are the achievement score obtained in the four tests and the results acquired from the two questionnaires.

Description and Characteristics of the Instrument

We have used two questionnaires in the empirical part of the research.

Questionnaire 1

The purpose of the first questionnaire was to establish student preferences during the learning process. In order to determine students' learning styles, we have used the VAK self-assessment questionnaire. This questionnaire asked respondents how they reacted in 25 different situations that directly or indirectly indicate the learning style that a person prefers. The respondents can be divided into one of three preferred styles of learning, and those are: visual, auditory and kinaesthetic style. This questionnaire was integrated into the Moodle system and students filled it out once they registered in Moodle.

Questionnaire 2

The second questionnaire consisted of four groups of questions which students filled out after the completion of the course.

The first group of questions referred to demographic characteristics of the respondents which consists of gender and age.

The second group of questions referred to the evaluation of the adaptive e-learning system. Students had to give their own estimation of how satisfied they were with certain aspects of the adaptive e-learning system. The satisfaction questionnaire consisted of 11 items which were anchored to a five-point Likert scale ranging from 5 (extremely satisfied) to 1 (not satisfied). The items of the questionnaire can be seen in Table 3.

The purpose of the third group of questions was to estimate the extent to which the adaptive e-learning system motivated students for studying. The learning motivation questionnaire included 11 items, and it was created especially for this research. The questionnaire was based on the Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items of the questionnaire can be seen in Table 4.

Reliability and Validity of the Scales

Since the questionnaires used for evaluation of system satisfaction and learning motivation have not been used with a larger population of students, and as their measurement properties were new to us, it was necessary to test their reliability and validity. The validity of the scales was tested with Principal Component Analysis and we estimated the reliability of the scales with Cronbach`s alpha.

Principal component analysis was used to determine the latent variables and to test satisfaction scale validity.

For the satisfaction scale, the analysis extracted 11 components, and only the first one had a characteristic root greater than 1. The first principal component had the largest proportion of variance, about 63%.

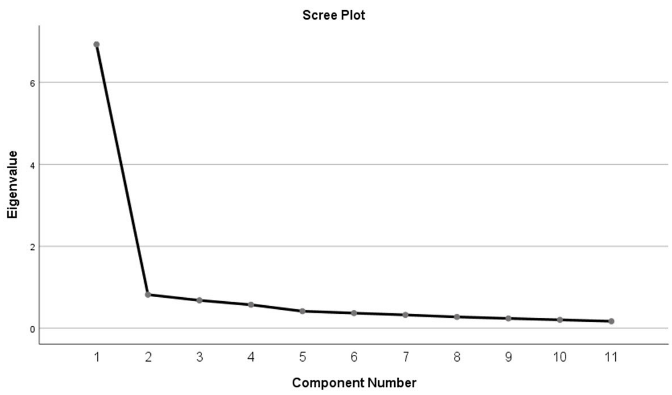

Figure 2. Screen plot

Based on the Scree plot we can see that the first component is significantly different from the others, and therefore we can say that this questionnaire had one principal component that dominantly defines its measure space. (Figure 2)

Table 3

The matrix of the first component structure (system satisfaction questionnaire)

Items	1
1. System quality	0.834
2. System organization (for example, the units and tests don't overlap)	0.811
3. Course content	0.845
4. Informing students (for example, pages with useful information and materials are available)	0.655
5. Lecture, teaching methods	0.851
6. Evaluation	0.821
7. Availability of resources	0.663
8. Group work	0.800
9. Acquiring practical knowledge	0.767
10. Teachers (for example, relation with students, communication, lectures...)	0.812
11. Teachers' support	0.839

All items in the satisfaction questionnaire were highly correlated with the first principal component. The largest contribution to defining the first component was made by items 5, 3, 11 and 1 (Table 3). Based on the structure matrix of the first principal component, we may say that all items in the questionnaire contribute to defining the first principal component, and this confirms the unique measuring tools of this questionnaire (Table 3).

Although the first principal component comprises 63% of the total variance, which means that part of the variability that describes satisfaction with the system was not covered with this component, we may say that this instrument is valid, especially when considering the high level of the saturation of the principal component with almost every statement in the questionnaire.

We estimated the reliability of the satisfaction questionnaire with Cronbach's alpha. The alpha coefficient for the satisfaction scale is very high 0.94. Therefore, we can say that the instrument was reliable at an acceptable level (DeVillis 2003; Kline 2005).

We also used Principal Component Analysis to test the validity of the learning motivation questionnaire and to determine latent variables of this questionnaire.

The analysis extracted 11 components, and only the first one has a characteristic root greater than one, i.e. the root value is 6.9. The first principal component has the largest proportion of variance, about 63%.

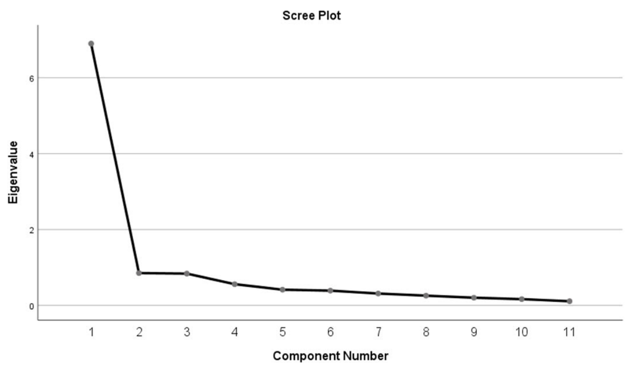

Figure 3. Screen plot

The scree plot confirms that the first principal component is significantly different from the other components, and thus we may say that this questionnaire has one principal component of measurement.

Table 4
The matrix of the first component structure (learning motivation questionnaire)

Items	1
1. The system motivates me to study more because it is interesting to use	0.849
2. The system motivates me to study more because it is more efficient than other systems	0.764
3. I would be more motivated for studying other subjects if they used this system	0.765
4. The information we need to acquire in this subject are well-organized in this system and thus I am more motivated	0.683
5. Faster progress that I have achieved with the use of this system motivates me	0.822
6. I am motivated to continue acquiring knowledge in this way	0.839
7. This learning system makes me understand lectures better and it motivates me to study	0.805
8. This learning system motivates me to study more	0.800
9. This learning system contributes to a better motivation of the entire group	0.760
10. I am motivated for further studying	0.923
11. I would recommend this learning system to others	0.666

We can see from the structure matrix that all statements in the questionnaire are highly and positively correlated with the first principal component. The first component is best defined with statements 10, 1, 6, 5 (Table 4).

Even though some statements are more dominant in defining the first principal component, we see that all statements contribute to defining the first component and this corroborates the unique measuring tools of this questionnaire.

Since the first principal component comprises 63% of the total variance, we may say that a part of the variability that describes student motivation is not covered with this component, but it is a smaller part of the variance, and we thus may say that this questionnaire had satisfactory validity, especially when considering the high level of the saturation of the principal component with the statements of this questionnaire.

We estimated the reliability of the learning motivation questionnaire with Cronbach's alpha. The alpha coefficient for learning motivation scale was very high (0.93). Therefore, we can say that the instrument was reliable at an acceptable level (DeVillis 2003; Kline 2005).

Thus, both scales showed a high level of reliability and satisfactory validity.

Results

Satisfaction with the Adaptive E-Learning System and Student Learning Motivation

The evidence provided in Table 5 shows that the majority of students were satisfied with the adaptive e-learning system. The students expressed the highest level of satisfaction with evaluation; teachers; teachers' support. However, the aspects of the system that could have been improved included informing students and acquiring practical knowledge; since students expressed the lowest level of satisfaction with these aspects.

Table 5
Students' satisfaction with the adaptive e-learning system

	Mean	Std. Deviation
System quality	4.00	1.080
System organization (for example, the units and tests don't overlap, etc.)	3.98	1.153
Course content	4.04	0.933
Informing students (for example, pages with useful information and materials are available)	3.71	1.236
Lecture, Teaching methods	3.94	0.998
Evaluation	**4.12**	**0.897**
Availability of resources	4.00	1.136
Group work	3.79	1.162
Acquiring practical knowledge	3.70	1.094
Teachers (for example, relation with students, communication, lectures...)	**4.39**	**0.792**
Teachers' support	**4.15**	**0.984**

The evidence provided in Table 6 shows that students were highly motivated to continue learning after they stopped using the adaptive e-learning system. The highest level of motivation was present in the following segments: "The system motivates me to study more because it is more efficient than other systems"; "I would be more motivated for studying other subjects if they used this system" and "I would recommend this learning system to others".

The lowest level of motivation was found with the following statements: "This learning system makes me understand lectures better and it motivates me to study" and "This learning system contributes to a better motivation of the entire group".

Table 6
Students' learning motivation

	Mean	Std. Deviation
The system motivates me to study more because it is interesting to use	3.92	1.141
The system motivates me to study more because it is more efficient than other systems	**4.25**	**0.937**
I would be more motivated for studying other subjects if they used this system	**4.32**	**1.022**
The information we need to acquire in this subject are well organized in this system and thus I am more motivated	4.06	1.085
Faster progress that I have achieved with the use of this system motivates me	4.00	1.097
I am motivated to continue to acquire knowledge in this way	4.16	0.998
This learning system makes me understand lectures better and it motivates me to study	3.79	1.112
This learning system motivates me to study more	3.97	1.147
This learning system contributes to a better motivation of the entire group	3.86	1.202
I am motivated for further studying	4.00	1.072
I would recommend this learning system to others	**4.21**	**1.079**

The Difference Between Score Means for Standard and Adaptive Modules

The first hypothesis of this research attempts to determine whether the implemented adaptive e-learning system provides a higher degree of knowledge and positively influences knowledge duration more than a standard non-adaptive e-learning system. To test this hypothesis, we used a t-test to analyse whether there are significant differences between mean scores for adaptive e-learning systems and non-adaptive e-learning systems. A significance level of 0.05 was used. S1 refers to the results of the test obtained immediately after the completion of the standard module of e-learning and A1 denotes the results of the test obtained immediately after the completion of the adaptive module. S2 refers to the results obtained a month after the completion of the standard module. A2 denotes the results obtained a month after the completion of the adaptive module.

All tests had the same number of questions (10) and they are scored in the same way (each question 1 point), and all the questions were of the same level of difficulty.

The mean values, standard deviations and standard errors of the mean for achievement scores after the S1, S2, A1, A2 tests are shown in Table 7.

Table 7
Mean values, standard deviations and standard errors of the mean for achievement scores

	Mean	N	Std. Deviation	Std. Error of the Mean
Scores on S1	8.14	228	1.244	0.082
Scores on S2	7.36	228	1.232	0.082
Scores on A1	8.88	228	1.157	0.077
Scores on A2	8.42	228	1.153	0.076

The mean score for the S1 test (8.14) is higher than for the S2 test (7.36). The mean score for the A1 test (8.88) is higher than for the A2 test (8.42). Based on the achievement scores, we can see that students achieved higher scores on tests (S1 and A1) carried out immediately after the compilation of both modules. Moreover, the results have shown that students had better results on both tests (A1 and A2) competed after the adaptive e-leaning module.

Table 8
Pearson's correlation coefficient between achievement scores on tests completed after the same module.

	N	Pearson's correlation coefficient	Statistical Significance (2-tailed)
Scores on S1 & Scores on S2	228	0.789	0.000
Scores on A1 & Scores on A2	228	0.906	0.000

Correlation is significant at the 0.01 level (2-tailed)

The correlation coefficient between tests S1 and S2 is statistically significant, of high strength (r =0.79) and positive. The correlation coefficient between tests A1 and A2 is also statistically significant, of high strength (r =0.91) and positive. Based on the obtained values of correlation coefficients between tests done after the completion of the same e-learning module, we may conclude that those students who have achieved higher scores on tests S1 and A1, have also achieved higher scores on tests S2 and A2. (Table 8)

The statistically significant difference in students` knowledge shown on tests S1, S2, A1 and A2 has been tested with the dependent t-tests, and the results are shown in Table 9.

Table 9
Dependent t-tests exploring mean differences between achievement scores

	t	df	Sig. (2-tailed)
Scores on S1 - Scores on S2	14.647	227	0.000
Scores on A1 - Scores on A2	13.921	227	0.000

Based on the received results we see that both t-tests are statistically significant which means that the differences between the achievement scores obtained in the different periods of time are statistically significant ($p<0.000$). Students achieved higher results and better knowledge on S1 and A1 tests. It should be emphasized that the difference between tests S1 and S2 is slightly higher than the difference between tests A1 and A2, and thus we may say that the adaptive module showed a smaller decrease in knowledge level.

Table 10
Pearson's correlation coefficient between achievement scores on tests completed after the deferent module

	N	Pearson's correlation coefficient	Sig. (2-tailed)
Scores on S1 & Scores on A1	228	0.725	0.000
Scores on S2 & Scores on A2	228	0.467	0.000

Correlation is significant at the 0.01 level (2-tailed)

The correlation coefficient between tests S1 and A1 is statistically significant, high in strength (r=0.73) and positive. The correlation coefficient between tests S2 and A2 is statistically significant, of slightly lower strength (r=0.47) and positive. Based on the correlation coefficients between tests done after different e-learning modules, we may conclude that those students who achieved better results on the S1 test, also did better the A1 test, and those who achieved better results on the S2 test also had better results on the A2 test. (Table 10)

Table 11
Dependent t-tests

		t	df	Sig. (2-tailed)
Pair 1	Scores on S1 - Scores on A1	-12.509	227	0.000
Pair 2	Scores on S2 - Scores on A2	-12.998	227	0.000

Table 11 shows the results for the dependent t-tests used to determine whether there were statistically significant differences between achievement scores on tests. Both t-tests have shown that there are statistically significant differences ($p<0.000$), which means that there is a statistically significant difference in students' knowledge acquired through the standard and adaptive module. The students performed better on the test completed after the adaptive e-learning module (A1 and A2).

The results indicate that H1 is accepted. The results above show that the adaptive e-learning module provides both a higher degree of knowledge as well as a more positive influence on the knowledge duration compared to a standard non-adaptive e-learning system.

The Relationship Between Learning Motivation and E-Learning Modules

We conducted multiple regression analysis to analyse the relationship between learning motivation and both e-learning systems. Moreover, we wanted to determine whether an adaptive e-learning system increases student learning motivation compared to a standard non-adaptive e-learning system. Student learning motivation was the criterion variable while achievement scores were the set of predictors.

Table 12
The multiple correlation coefficient

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.283	0.180	0.064	9.08128

Table 13
The statistical significance of the regression model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1606.050	4	401.513	4.869	0.001
	Residual	18390.735	223	82.470		
	Total	19996.785	227			

The regression model is statistically significant at level $p=0.001$. Multiple correlation coefficient is $R=0.283$ and set of predictors explains about 18% of the variability of system variables. Based on these results we may say that there is a lower level of relationship between the criteria and the set of predictor variables. (Table 12 and Table 13)

Table 14
The partial contribution of the predicators

	Beta	**t**	**Sig.**
(Constant)		5.107	0.000
Scores on S1	-0.124	-0.983	0.327
Scores on A1	0.306	1.786	0.075
Scores on A2	0.203	1.931	0.050
Scores on S2	-0.089	-0.584	0.560

Statistically significant partial effect on the prediction of criterion variable is achieved with the test A2 which has a beta coefficient of 1.203, significant at level $p=0.05$, while the test A1 is weakly statistically significant at $p=0.75$. Tests S1 and S2 do not have a statistically significant effect on the prediction of the criterion variable. Tests A1 and A2, completed after the adaptive e-learning system, show a tendency to have a positive effect on student learning motivation. Furthermore, the higher scores students had, the level of their motivation to use the adaptive module increased. Tests S1 and S2, completed after a standard non-adaptive module, have not displayed a statistically significant effect on student learning motivation (Table 14).

The results support the hypothesis that the adaptive e-learning module increases student learning motivation is accepted.

Relationships Between Learning Styles and the E-Learning Model

We used Canonical Discriminant Analysis to test the relationship between learning style and the use of the e-learning module. The group variable was learning style, while test scores were the set of predictor variables.

Table 15
Eigenvalue, Percentage of Variance and Canonical Correlation

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	0.071a	85.3	85.3	0.258
2	0.012a	14.7	100.0	0.110

Canonical discriminant analysis extracted two discriminant functions and only one of them was statistically significant. (Table 15)

Table 16
The level of significant of discriminant functions

Function	Wilks' Lambda	χ^2	df	Sig.
1	0.922	18.104	8	0.020
2	0.988	2.724	3	0.436

The first discriminant function is statistically significant at significance level p=0.02 and with canonical correlation coefficient Rc=0.258 which means that there is a difference among student groups and that this difference is of lower intensity. In our further analysis, we will take into consideration only the structure of the first discriminant function. (Table 16)

Table 17
Structure matrix of the first discriminant function

	Function
	1
Scores on A1	0.790*
Scores on A2	0.608*
Scores on S1	0.470*
Scores on S2	0.412

All predictor variables are on the positive pole of the discriminant function. This function is best defined with the score on the tests A1 and A2, and the scores on these tests have the highest scores on the discriminant function. (Table 17)

Table 18
Functions at Group Centroids

Learning styles	1
Visual	-0.020
Auditory	-0.227
Kinaesthetic	0.415

Based on the values and directions of the group centroids, we may say that students with a kinaesthetic learning style show somewhat better results on all tests in comparison to students who prefer the other two styles. The group of students with a kinaesthetic learning style is on the positive pole of discriminant function (0.42), unlike the other two groups of students who are on the negative pole of discriminant function. Students with a visual learning style (- 0.02) have better test results than students with auditory style and worse than students with kinaesthetic learning style. Students with an auditory style have the greatest centroid value on the negative pole of discriminant function (- 0.227) which means that they have the worst results on all tests compared to the other two groups of respondents.

The results support the hypothesis which says that there is a statistically significant relationship between learning styles and achievement scores on the A1, A2, S1 and S2 tests.

The Relationship between Gender, Learning Motivation, Achievement Scores and Satisfaction with the Adaptive E-Learning System

We conducted a series of independent samples t-test to analyse if there is a statistically significant gender difference in motivation, achievement scores on tests and satisfaction with the adaptive e-learning system.

Table 19

Mean values, standard deviations and standard error of the mean for both female and male respondents

	Gander	Mean	Std. Deviation	Std. Error of the Mean
Scores on S1	Female	8.20	1.197	.125
	Male	8.10	1.278	.110
Scores on A1	Female	8.87	1.141	.119
	Male	8.89	1.172	.100
Scores on S2	Female	7.30	1.193	.124
	Male	7.40	1.261	.108
Scores on A2	Female	8.39	1.176	.123
	Male	8.44	1.140	.098
Learning motivation	Female	45.4239	7.75197	.80820
	Male	43.9265	10.32984	.88578
Satisfaction	Female	45.4783	6.20613	.64703
	Male	42.7059	10.38811	.89077

Based on the mean values we may conclude that respondents of both genders have almost equal average grades on all tests. As seen in Table 19, females show on average a slightly bigger learning motivation than male respondents. A similar situation can be found with satisfaction with the adaptive e-learning system. Female students show a higher level of satisfaction than male students. Statistical significance of these differences has been tested with t-tests (Table 20).

Table 20

Independent samples t-tests exploring mean differences between genders

	T test	df	Sig.	Mean Difference	Std. Error Difference
Scores on S1	.551	226	.582	.093	.168
Scores on A1	-.129	226	.898	-.020	.157
Scores on S2	-.557	226	.578	-.093	.167
Scores on A2	-.320	226	.749	-.050	.156
Learning motivation	1.183	226	.238	1.49744	1.26587
Satisfaction	2.297	226	.023	2.77238	1.20717

The results show that there is only a statistically significant difference in the satisfaction with the adaptive e-learning system, i.e. female respondents show greater satisfaction with the adaptive e-learning system.

The received results give partial support to the hypothesis regarding gender differences, and only regarding students' satisfaction with the system.

Discussion

The results of the research have confirmed our expectations and have shown that an adaptive e-learning system can increase students' learning results.

The study has shown that students performed better on the test that they completed after adaptive e-learning module.

Our paper found a number of results that support this conclusion.

First, our study has found that the adaptive e-learning module provides at the same time a higher degree of knowledge and more positively influences the knowledge duration than a standard non-adaptive e-learning system. Prior research on this subject has shown contradictory findings. Coffield et al. (2004) believe that the reason for these contradictory findings lies in the fact that in most of studies the size of a sample was very small, and because respondents were exposed to an adaptive e-learning module for a very short period of time. However, a certain number of researches came to the conclusion that students exposed to adaptive e-learning systems achieved better results than those who were not (Barjaktarević, Hall and Fullick, 2003; Brown et al., 2006; Brown, 2007; El Bachari, Abelwahed and El Adnanii, 2011; Graf, 2007; Graf, Kinshuk and Liu, 2009; Klašnja-Milićević et al., 2011; Latham, Crockett and McLean, 2014; Popescu, Badica and Moraret, 2010; Sangineto et al., 2008; Siadaty and Taghiyareh, 2007; Tseng et al., 2008; Wolf, 2007), and this is in line with the results of our research.

Second, the results have revealed that there is a statistically significant relationship between student learning motivation and the usage of an adaptive e-learning system, while it is not the case with a standard e-learning system. The achievement scores on both tests completed after the adaptive e-learning module have shown a positive effect on student learning motivation. Therefore, we have concluded that an adaptive e-learning system increases student learning motivation.

Third, we have identified that an adaptive e-learning system has different effects on students with different learning styles. Students with a kinaesthetic learning style show better results on all tests in comparison to students of the other two styles. On the other hand, students with an auditory learning style achieved the worst performance on all tests. Although there haven't been many studies that have analysed the effects of students' learning styles on their performance in the context of adaptive e-learning, Graf, Kinshuk and Liu (2009) discovered that adaptive e-learning system can have different effects on students with different learning styles.

Finally, the results of the study have indicated that there is a difference between genders regarding learning motivation, achievement scores on tests and satisfaction with an adaptive e-learning system. Although female respondents have obtained slightly higher than average scores on tests and expressed a slightly bigger motivation than male respondents, there is only a statistically significant difference in the satisfaction with an adaptive e-learning system. Namely, female students have expressed a higher level of satisfaction with the system.

In general, the majority of students have expressed a high level of satisfaction with an adaptive e-learning system which is in correspondence with previous research. Some of the previous studies have also shown that both teachers and students who used adaptive e-learning systems have expressed a high level of satisfaction with the system (Jovanović, Gašević and Devedžić, 2009; Limongelli et al., 2009; Latham et al., 2012; Limongelli et al., 2011; Özyurt, Özyurt and Baki, 2013; Sevarac, Devedzic and Jovanovic, 2012; Mustafa and Sharif, 2011).

Conclusion

For the purpose of this research, we designed a model of an adaptive learning management system (LMS) and implemented it in Moodle. The developed model of adaptive e-learning is based on the VAK learning style model. The identification of a student's learning style has been proven to increase student learning effectiveness. In general, an adaptive e-learning system enables more meaningful learning since it improves flexibility, provides participation, interaction and real-time feedback (Kamardeen, 2014).

In this paper, we have analysed the effects and effectiveness of an adaptive e-learning system. We have discovered that there are significant differences in learning effectiveness, satisfaction and motivation when students use an adaptive e-learning module in comparison to a standard e-learning module. Moreover, we have investigated the effectiveness and the durability of knowledge acquired with an adaptive e-learning system by comparing the performance of students not only after the completion of the course but also a month after the course.

So far, to our knowledge, no study has evaluated the performance between a control and experiment group a few months after the completion of the course, i.e. they haven't analysed the durability of the knowledge acquired through an adaptive e-learning system. Moreover, the motivation of students to continue using an adaptive e-learning system hasn't been analysed so far.

There are several limitations to the study. The first limitation refers to the sample. The same students represented the control and experiment group. For further research, we would recommend that students are divided into two groups, one would be a control group and another an experiment group. Both groups would attend the same course for one semester, but a control group would be presented with a standard e-learning course and an experiment group with an adaptive e-learning course. The adaptive e- learning course would match learning styles of the experiment group.

The second limitation is in regards to the model of an adaptive e-learning system. Our model diagnoses a student's learning style as a measuring instrument, i.e. the VAK questionnaire. We propose that future research use an implicit method, i.e. analyse the behaviour of students and in that way identify their learning styles. By implementing the implicit method in the model, we would avoid psychometric disadvantages of traditional measuring instruments and the model wouldn't be static, i.e. it would regularly update information about student behaviour.

The study leaves a certain space for further growth. First, since our study has shown that there are differences regarding students' performance amongst students with different learning styles, further research can deal more thoroughly with the advantages and potentials of adaptivity regarding students' learning styles. Secondly, other student characteristics, besides learning styles, could be considered when developing an adaptive e-learning system. Those student characteristics could include previous knowledge, student interests, the speed of learning, etc.

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Conflict of interests

The authors declare no conflict of interest.

Author Contributions

Conceptualization, I.R., and M.R.R.; methodology, I.R., and V.T.; software, I.R., and M.B.; formal analysis, M.R.R., T.S.T., and M.B.; validation, I.R., T.S.T., and V.T.; writing—original draft preparation, I.R., M.R.R., T.S.T., V.T., and M.B.; writing—review and editing, M.R.R., T.S.T., and I.R.. All authors have read and agreed to the published version of the manuscript.

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