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Improve estimated time-on-task calculation in a Virtual Learning Environment

Abstract

The main aim of this paper is to present results of an experimental test focused on the validity and effectiveness of composed methodology aimed at increasing the student's attention in Virtual Learning Environment. Areas of presented methodology which were subject of our research is students behavior during learning. The behavioral part of methodology is focused on calculating estimated time for reading/learning specific learning material based on mathematical model. The model has been created as linear regression model trained and validated with student’s access logs from LMS Moodle instance used at the university. The methodology created by us, which is the subject of the experiment, uses the mentioned mathematical model in order to more optimally calculate the time-on-task and thus assume the time required for the correct understanding of the presented curriculum in the form of e-learning.

In this paper, we will focus on confirming the didactic effectiveness of our proposed methodology for monitoring student attention. We describe an experiment with which we verified the proposed methodology. Methodology itself is focused on improving students learning experiences while using e-learning platforms like LMS Moodle.

Keywords: e-learning, time-on-task, structural evaluation, experiment, Moodle

Introduction

The use of e-learning in today's education is already an integral part of the educational process. We can primarily speak of universities, but also of other state-funded institutions focused on education, as well as private companies, which can be defined as "educational institutions" (Bates, 2005). At the same time, it should be noted that from the infrastructure point of view, the widespread use of e-learning in any developed nation is not a problem. This statement is supported by the fact that for example in Slovakia more than 74% of educational institutions, by which we mean all levels from kindergartens to universities, have the opportunity to integrate e-learning into the education process (Institute of Education Information and Forecasting, 2015), while at universities this number is 100%.

One of the anticipated problems that prevent the full use of the educational potential of e-learning is the insufficient feedback of the student towards the teacher. Also non-deterministic guidelines for content improvement from a formal point of view differ in each country. Application practice has shown us that currently, the only effective tool that allows us to realistically monitor the study progress of the student during the education itself is a continuous evaluation of inappropriately determined periods within the study (Sotirova, 2019). Two key factors are essential in this assessment of the knowledge acquired so far:

1. setting the right time intervals,
2. determining the right content.

We must implement this method directly into the educational process already during the design of the study plan. Thus, it is necessary to set aside time for the above testing to take place within the study.

We present an alternative way of obtaining feedback, by monitoring the student's activity during the learning process itself, based on maintaining the student's attention in the education process, thus improving the student's ability to master the presented curriculum. This paper aim is to present a methodology for maintaining the attention of students of the e-learning course. In this paper, we statistically proved that better learning outcomes were found in study groups that worked with the support of this methodology.

The article is divided into 5 chapters. After an introduction and a description of similar works that inspired us, the methodology section follows. It provides a more detailed description for calculating the estimated time spent on the study content page. This is important to determine when, in our opinion, the student is losing attention. To verify our methodology, a module was created for the Moodle e-learning environment. Our main ideas were incorporated into it. In the results chapter, we present a statistical comparison of the control group and the experimental group. A module created by us was implemented for students of the experimental group. At the end of the article, we present a discussion at the end.

Related work

The main problem, which many times make it impossible to compile an exact formula identifying a student's behaviour, is the very essence of the educational process. The individual nature of this activity is a major obstacle to the unification of any predictive mechanisms based on data analysis. In addition to the use of trace data which can be then easily converted to aggregate numerical output, virtual learning environments (VLE) trace data has been extensively used to estimate students actual time spent online as a proxy of academic activity and learning. One of the primary ways of improving student learning is to develop learning activities that support longer engagement periods with course content or peers (Stallings, 1980). Instead of using count measures, time-on-task measures provide a more “accurate” estimate of the effort students spent learning.

Time-on-task

There is a long convention for the utilization of time in educational research (Jez, 2015). One of the first concepts are dated to 1963 when Carroll proposed a model of learning where time was a focal component, and learning was characterized as a function of the exertion spent according to the exertion required. This author also defined two main variables which cannot be confused:

- elapsed time – total time student spent on learning activity,
- actual-time - time students spend on learning.

A principle challenge with research on the impacts of time on learning is distinctive operationalization of the time-on-task construct. A group of scientists (Helmke, 1986; Cohen, 2007) utilized ordinary observational strategies, for example, checking student behaviour at indicated time intervals and coding that conduct utilizing a predefined coding plan. Others (Admiraal, 1999) adopted altogether different and cruder ideas of time-on-task, such as the number of lectures joined, the number of school days in a year, or hours in a school day. As called attention to by Karweit and Slavin (1982), contrasts in meanings of on-task and off-task behaviour, perception spans, and test sizes prompted significant irregularities in this research domain.

Despite prior warnings by Karweit and Slavin in their study from 1982 regarding time-on-task estimation, novel empirical studies (Calderwood, 2014; Judd, 2014; Rosen, 2013) continues to illustrate the complexities and possible inaccuracies linked to time estimation in the digital age. Given the ubiquitous access to technology, student learning activities are characterized by high levels of distraction and multi-tasking, which are shown to have negative effects on student attention and learning (Bowman, 2015). Similar results were found by Judd (2014), who looked at the levels of student multi-tasking while engaged in a learning activity. Using a specifically designed tracing application installed on the computers of 1 249 participants, Judd noted that Facebook users spent almost 10% of their study time on Facebook rather than studying. Also, 99% of student study sessions involved some form of multi-tasking. Whatever "correct" distraction times maybe, today's students are certainly engaging in much more multi-tasking and off-task behaviours that affect the accuracy of measuring student time-on-task. We should note that in this context "off-task" should be understood as "off-system" meaning that students spend some time outside the system. This does not necessarily mean not engaging in productive learning activities (e.g., reading a printed document or attending a study group meeting), however, given that time-on-task estimates are used to understand learning activities and often to build predictive models of student success or identify students at risk, there is a need to provide better estimates of students' time-on-task (Kovanović, 2015).

The recently depicted observational methods have additionally been utilized in numerous research papers (Baker, 2004; Smeets, 2000; Worthen, 1994) for assessment of student conduct and time-on-task examination when working with educational technology. For example, research in the area of Intelligent Tutoring Systems (ITS) has looked to distinguish off-task conduct and its consequences for learning (Baker, 2007; Cetintas, 2010; Cetintas, 2009; Pardos, 2013; Roberge, 2012). The reception of educational technology has empowered a moderately simple count of student time-on-task dependent on the trace data gathered by the e-learning software platform. Grabe (2002) used several heuristics for time-on-task estimation:

1. all learning actions longer than 180 seconds were estimated to be 120 seconds long,
2. all multiple choice answering actions to be at a maximum of 90 seconds,
3. last actions within each study session were estimated at 60 seconds.

Each week, students attended two lectures and one small group discussion section, however, this study concerns only the lecture component of the course. Performance in the lecture component was evaluated using multiple-choice examinations and accounted for 75% of the points determining final grades. The book, In Search of the Human Mind from Sternberg (1998), was required reading for the lecture component of the course.

Later exploration in the ITS field has prompted the improvement of a few artificial intelligence frameworks for machine learning systems of student off-task conduct dependent on trace data. The development of such models was made possible due to the availability of field observational data, thereby providing a "gold standard" for testing the performance of different models.

In his study, Baker (2007) identified a time of 80 seconds to be the best cut-off threshold for the identification of off-task behaviour. This research provides an empirical analysis of the different approaches for the detection of off-task behaviour and lays the groundwork for reproducible and replicable research in the ITS field.

Web usage and Educational data mining

User activities are extensively analyzed in the area of Web Usage Mining (WUM) (Cooley, 1997), which is defined as "the automatic discovery of user access patterns from Web servers". Data pre-processing is recognized as a crucial step in WUM analysis (Munk, 2011; Munk, 2010) and it is estimated to take typically between 60% and 80% of the total analysis time (Hussain, 2010; Marquardt, 2004).

Of direct importance for the studies presented in this paper is the notion of different strategies for session identification:

- time-oriented heuristics - which place an upper limit on the total session time (typically 30 minutes), or an upper limit on a single Web page time (typically 10 minutes) (Cooley, 1999; Mobasher, 1999).
- navigation-oriented heuristics - which look at web page connectivity to identify user sessions. When for the same IP address two consequent pages in the access log are not directly linked, then this signals the start of a new user session.

As pointed out, time-oriented heuristics are simple, but often unreliable, as users may undertake parallel off-task activities. Hence, it can be problematic to define user sessions based on time. Munk (2010) adopted 10-minute timeout intervals for session identification and identified path completion pre-processing as an important step for improving the quality of extracted data. With the migration to Web-based learning platforms and with the more extensive selection of VLE, a group of researchers (Ba-Omar, 2007) have embraced customary WUM methods to break down learning data.

Perhaps the enriching study in the context of learning, which tended to student time-on-task is by Marquardt, Becker, and Ruiz (2004). Their methodology is special in offering an alternate conceptualization of user session. The creators use a reference session to show a regular user session, and a learning session to demonstrate a user session spreading over numerous days and concentrating on a specific learning action.

Notwithstanding the work drawing on research from Web mining, there are likewise later studies from the fields of learning analytics (LA) and educational data mining (EDM) that receive novel procedures to address the issues of time-on-task estimation. For example, the research done by Del Valle (2009) detailed the utilization of a 30-minute timeout interval to distinguish the end of student session, and for every session assessed the span of last activity as a normal time spent on a given activity by a specific user. The author also calls attention to finding that the assessment of student time-on-task dependent on trace data is made under the presumption that time between two logged events is spent on the learning and that similar assumptions are made in the research of other learning modalities.

Several researchers have embraced novel strategies for time-on-task assessment. For example, Brown (2009) determined time spent perusing conversations by extricating the average number of words per conversation and afterwards multiplying it by 180 words per minute (which was obtained empirically). The problematic part of this methodology is in its failure to identify shallow reading and skimming (i.e., reading that is faster than 6.5 words per second) (Hewitt, 2007), as done in comparative studies (Oztok, 2013; Wise, 2013) that estimated time-on-task from trace data. A few studies likewise utilized self-revealed data on the number of time students spent using the selected e-learning platform (e.g., García-Martín, 2013; Hsu, 2013; Romero, 2011), and this methodology raises an extra arrangement of reliability challenges (Winne, 2002). Finally, in the laboratory environment, Guo (2009) and Kolloffel (2011) estimated time-on-task as the distinction between the beginning and the finish of an experimental learning activity.

Methodology

An important part of the method for identifying loss of attention was the creation of a model for calculation estimated time spent on educational content/page. Dataset for model creation was

obtained from the VLE log file. The data preparation within the VLE (in our case Moodle) is partly different from the data preparation obtained directly from the web server log file (Drlík, 2014). In our case, we obtained a set of data representing the access logs of individually registered VLE users at edu.ukf.sk, in the period 2007-2014. The total number of examined records was 4 698 524. We had to subject the data obtained in this way to the cleaning process. These were not only standard reasons, such as the deletion of teacher access records but also the removal of certain duplications due to possible errors in storing these records.
At this phase, we were able to accurately define four main variables:

- Time spent on educational material;
- Number of words (only related to educational purposes) of educational material;
- Number of images (only related to educational purposes) of educational material;
- Page number.

We also tried to extract more attributes like the number of animations (flash apps), number of videos etc. The problem was that we were unable to extract the numbers correctly because many times course authors and tutors responsible for creating the educational material used embedded code which we were unable to identify via XPath or SQL queries. So we decided to leave extraction of these attributes as a subject of further research.

Estimated time spent on the educational material using the regression model
At this point, we have structured data that can be used as an input for the model for calculating the estimated time spent on an educational content/site. We chose regression from several methods, mainly because of its simplicity. The total number of records was 50 346. For this purpose, we developed a small application in Python 3. The application used multiple Python dependencies like Numpy or Pandas. However, the most important one is Scikit-learn. Based on research done by Skalka (2019) we considered multiple different approaches usable for our needs. Given that the prerequisites for the use of linear regression were met, we chose a Linear Model class. The main reason for choosing this specific analytical method is that we know that the relationship between the independent and dependent variable have a linear relationship based on the results from the descriptive statistics. Based on the nature of this relationship, we did not have to choose a more complex analytical method. The input data we used in the ratio of 80% for training and 20% for testing. The rounded predicting accuracy was 71.86% after training this model. The level of predicting accuracy could be better if we would include more attributes or include more data to training input. Thanks to these findings, we were able to identify the relationships between the structural nature, the extent of educational materials and the time students spend on these educational materials during teaching. The formula for verifying the correctness of the calculation of the Assumed Time Spent (*ATS*) is

$$ATS = (0.04065806\,ECL) + (3.4554037\,\mathrm{NoI}) + \ 65.00134174,$$

where *ECL* (Educational Content Length) is the number of words found in the section intended for education and *NoI* (Number of Images) is the total number of images placed in the educational section of presented content(images in header etc. were excluded).

Moodle module implementing a defined methodology
The model for calculating the *ATS* variable was key to creating a module that identifies students' loss of attention. We developed a new module for LMS Moodle (CONTRIB-8078) which implements created methodology. The module uses JavaScript technology to determine whether the student has a constantly active card with educational content and at the same time, the module calculates the current time the student spent on educational content. During the study, the student is practically unaware that he is being monitored. The change will not take effect until the student exceeds the calculated estimated time spent on educational materials. As soon as the current session

on the specified page exceeds the number of seconds calculated by the system, the student's helper, defined by the teacher for the activity, will be displayed. The assistant has the task of partially entertaining the student, as well as providing information in other ways. Similar activating elements increase the student's attention and prevent him from falling into a state of boredom. However, learning of more complicated educational units remains a problem. In such a case, it is quite possible that, despite the great efforts of the teacher to simplify the substance in the educational materials, the limit will be exceeded. This fact has occurred several times. Over time, students stopped perceiving the helper positively, but rather as an element that distracted them. Supported Moodle activities were:

- Book;
- Page;
- Lesson;

We solved this problem by adding more graphical forms of helpers and selecting them at random. So, in addition to the helper message, which was to enrich the student and show the issue a little differently, we also changed the graphic presentation. Thanks to this variation, the desired effect of changing the graphic stimulus were preserved, and thus increasing the student's attention during the study. This can be stated based on the results of a questionnaire filled out by students at the end of the semester. If the teacher does not prepare any helper messages, the module still monitors the student's activity, but no action is taken when the deadline is reached. At the same time, the module treats various conditions that may occur and be evaluated as the study of educational material, while the student does not pay attention to the relevant activity. It simplifies the data presented to easily interpreted information. After leaving the course and viewing additional sources which may help the student understand the presented topic, the countdown will stop. As such, the module takes into account that the student is actively studying the educational material, only if the student has the active educational material open in front of him. All other scenarios are considered incorrect. At the same time, the next iteration of the countdown will only start when the student helper is closed. This gives us the certainty that the student did not leave the computer, and thus does not distort the results.

Results

Data understanding

We verified the suitability of the created module by experiments. This took place in the winter semester of 2019/2020. The experiment was attended by 36 students of the second year of master's studies in age from 22 to 23 years in the field of Applied Informatics. During the semester, we monitored two groups of students in the course Advanced Web Technologies, which were created by random assignment to groups. The students were divided into the following groups:

- the group marked UT01 - in this group, we implemented the teaching process with the support of the created module, and based on the calculated estimated time spent studying the educational material, students were confronted with individual auxiliary reports when this time was exceeded,
- the group marked UT02 - group was not influenced in any way by the module we created during teaching.

The UT01 group represents an experimental group, and the UT02 group represents a control group. In our case, we performed the initial evaluation of knowledge by a theoretical test. The rating scale was from 0 - 60 points. The test was implemented as an activity in Moodle. There were several types of questions in the test, namely:

1. Multiple choice question;
2. Short answer question;
3. Questions with options True / False.

The results of the pretest, i.e. the obtained evaluations in both monitored groups are clearly shown in the descriptive statistics (Tables 1 and 2).

Table 1: Descriptive statistics of pretest score - control group

	Valid N	*Mean*	*Median*	*Minimum*	*Maximum*	*Lower Quartile*	*Upper Quartile*	*Range*	*Quartile Range*	*Coef.Var.*	*Skewness*	*Kurtosis*
pretest (max 60)	15	40.80	41.00	29.00	51.00	32.00	49.00	22.00	17.00	18.88	-0.10	-1.47
pretest (%)	15	68.00	68.33	48.33	85.00	53.33	81.67	36.67	28.33	18.88	-0.10	-1.47

Table 2: Descriptive statistics of pretest score - experimental group

	Valid N	*Mean*	*Median*	*Minimum*	*Maximum*	*Lower Quartile*	*Upper Quartile*	*Range*	*Quartile Range*	*Coef.Var.*	*Skewness*	*Kurtosis*
pretest (max 60)	19	43.26	44.00	24.00	54.00	37.00	52.00	30.00	15.00	19.84	-0.61	-0.33
pretest (%)	19	72.11	73.33	40.00	90.00	61.67	86.67	50.00	25.00	19.84	-0.61	-0.33

Based on the data from the descriptive statistics, we see certain indications concerning the monitored variables. When comparing the results found in Table 1 and Table 2, we can state the following:

- looking at the estimates of the mean values (Mean and Median) we see small differences in favour of the experimental group,
- based on the value of the coefficient of variation (Coef.Var.). As well as the quartile range (Quartile Range), we see that in the experimental group, the results were slightly more homogeneous compared to the control group.

Given the need to verify the equivalence of both groups, we decided to establish a null hypothesis as follows:

H0: The UT01 group and the UT02 group, are equivalent in the level of achieved knowledge in the field of programming in PHP and JavaScript programming languages and theoretical knowledge in the field of web application development.

This means that the pretest results do not depend on the group factor. In our case, we carried out the final evaluation of the subject by evaluating the created student applications and the results from application presentation. It follows that the final subject grade consists of 2 parts:

- Results of application evaluation;
- Results of final application presentation;

The rating scale of the application evaluation was from 0 - 100 points. The evaluation was carried out as the average value of evaluations of individual members of a three-member committee consisting of experts (2 teachers and 1 expert from practice) in the field of web application development. The assignment, for students, for the creation of the application was a real assignment. This fact improves students' motivation to learn, mainly because students solve a real problem from practice. The commission evaluated several aspects of the application, with each aspect of the application having its evaluation criteria. These criteria were set at the beginning of the semester as follows:

- Environment installation and configuration - 5 points;
- The correct way to define the database layer (migration, seeds) - 10 points;
- Comprehensive use of MVC architecture (in the view files there will be only graphic parts,

models will contain only business logic, etc.) - 50 points;
- Use of Blade when creating view files - 20 points;
- Fully meet the acceptance criteria for the application - 15 points.

Posttest results, i.e. the obtained evaluations in both monitored groups are clearly shown in the descriptive statistics (Tables 3 and 4).

Table 3: Descriptive statistics of the posttest score - control group

	Valid N	*Mean*	*Median*	*Minimum*	*Maximum*	*Lower Quartile*	*Upper Quartile*	*Range*	*Quartile Range*	*Coef.Var.*	*Skewness*	*Kurtosis*
posttest (max 100)	15	61.27	65.00	0.00	100.00	50.00	91.00	100.00	47.00	58.46	-0.84	-0.40
posttest (%)	15	62.61	67.53	0.00	100.00	50.67	88.47	85.67	37.80	46.45	-0.74	-0.56

Table 4: Descriptive statistics of the posttest score - experimental group

	Valid N	*Mean*	*Median*	*Minimum*	*Maximum*	*Lower Quartile*	*Upper Quartile*	*Range*	*Quartile Range*	*Coef.Var.*	*Skewness*	*Kurtosis*
posttest (max 100)	19	77.32	79.00	0.00	100.00	72.00	85.00	100.00	13.00	27.44	-2.76	-10.4
posttest (%)	19	76.27	79.13	0.00	100.00	72.93	85.13	86.67	12.20	23.10	-3.07	-11.9

Based on the data from the descriptive statistics, we see certain indications concerning the monitored variables. When comparing the results found in Table 3 and Table 4, we can state the following:

- the average number of points obtained in the post-test was higher in the experimental group than in the control group,
- the quartile margin decreased markedly in the experimental group,
- students achieved markedly more stable results in the experimental group than students in the control group.

Based on the data survey, we decided to establish a null hypothesis. For the posttest, we set the null hypothesis as follows:

H0: The UT01 group and the UT02 group, are equivalent in terms of the level of knowledge in the field of programming in PHP and JavaScript programming languages and theoretical knowledge in the field of web application development, even though the UT01 group completed their studies with the help of formally modified educational materials as well as the active work of the module during the teaching process.

This means that the results of the posttest do not depend on the group factor. Based on the obtained data, it can be preliminarily assumed that students exposed to the influence of our defined methodology of editing the formal content of educational materials, as well as increasing attention with the help of the module created by us achieved better study results than students who were not exposed to this influence. In a more detailed analysis, we see that based on the results of descriptive statistics, both groups are equivalent in the results of the pretest, i.e. in the level of achieved knowledge in the field of programming in PHP and JavaScript programming languages as well as theoretical knowledge in the field of web application development.

Data analysis

The basic step necessary for the application of any parametric statistical method is the normality test. The reason is to verify the assumption that the data we tested come from a basic statistical file with a normal distribution. Based on the previous information, we assume that the variable we set will not have a normal distribution. In our case, the Shapiro-Wilk test was used.

Table 5: Verification of the presumption of normality of the control group

	N	*Shapiro-Wilk's W*	*p*
pretest (max 60)	15	0.920763	0.197864
pretest (%)	15	0.920763	0.197864
posttest (max 100)	15	0.849665	0.017178
posttest (%)	15	0.886865	0.060136
Grade	15	0.878434	0.044963

Table 6: Verification of the assumption of normality of the experimental group

	N	*Shapiro-Wilk's W*	*p*
pretest (max 60)	19	0.929211	0.167484
pretest (%)	19	0.929211	0.167484
posttest (max 100)	19	0.687045	0.000039
posttest (%)	19	0.660543	0.00002
Grade	19	0.566818	0.000002

Table 7: Verification of the assumption of normality of the research sample (exp. and cont. groups)

	N	*Shapiro-Wilk's W*	*p*
pretest (max 60)	34	0.944474	0.083857
pretest (%)	34	0.944474	0.083857
posttest (max 100)	34	0.782693	0.000012
posttest (%)	34	0.803145	0.000029
Grade	34	0.783341	0.000012

Based on the results presented in tables 5, 6 and 7, we see that the value of *p*, which determines the statistical significance, reaches a value of less than 0.05 for the grade and test variables. Values greater than 0.05 are statistically insignificant. In these cases, we do not reject the null hypothesis, which assumes a normal distribution of the investigated variable. Based on the above test, we see that in our case, the assumption of normality in the case of the variables mark and results of the posttest is violated, i.e. it is not possible to use parametric procedures, e.g. t-test for independent samples, to verify our research assumptions/hypotheses.

A non-parametric alternative to the two-sample t-test is the Kolmogorov-Smirnov two-sample test. The values monitored by us are primarily the achieved results from the posttest as well as the final mark, which reflects the total achieved result within the mentioned testing.

Table 8: Results of the Kolmogorov-Smirnov two-sample test

	Max Neg Differnc	*Max Pos Differnc*	*p-value*	*Mean contr*	*Mean exp*	*Std.Dev. conrt*	*Std.Dev. exp*	*Valid N contr*	*Valid N exp*
pretest (max 60)	-0.26316	0.052632	p > 0.10	40.8	43.26	7.7	8.58	15	19
pretest (%)	-0.26316	0.052632	p > 0.10	68	72.11	12.84	14.3	15	19
posttest (max 100)	-0.480702	0.122807	p < 0.05	61.27	77.32	35.82	21.22	15	19
posttest (%)	-0.494737	0.175439	p < 0.05	62.61	76.27	29.08	17.62	15	19
Grade	-0.052632	0.414035	p > 0.10	1.67	1.42	0.62	0.56	15	19

The given information, specifically the achieved marks of students and the results of the posttest, found in Table 8, we have visualized in the form of a graph for a better understanding

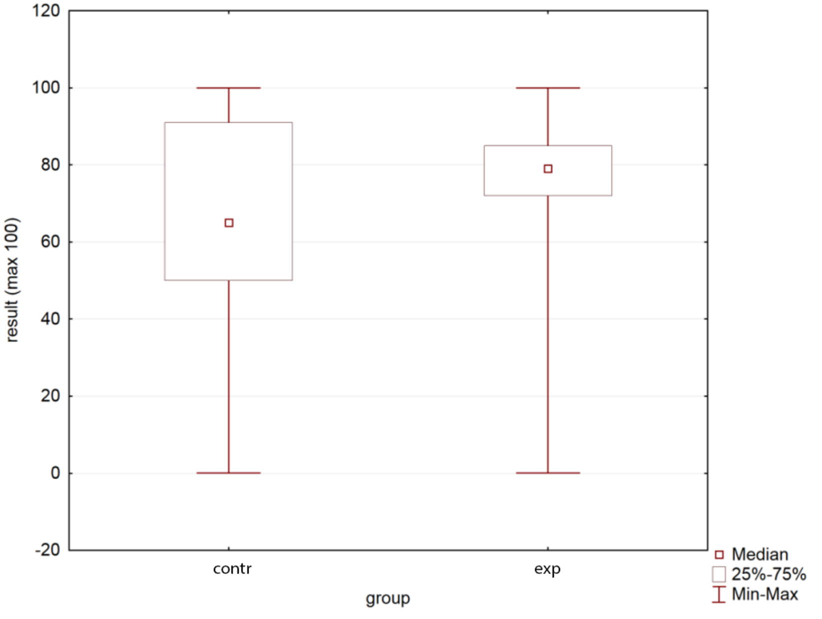

Figure 1: Visualization of the achieved posttest results for the control and experimental group

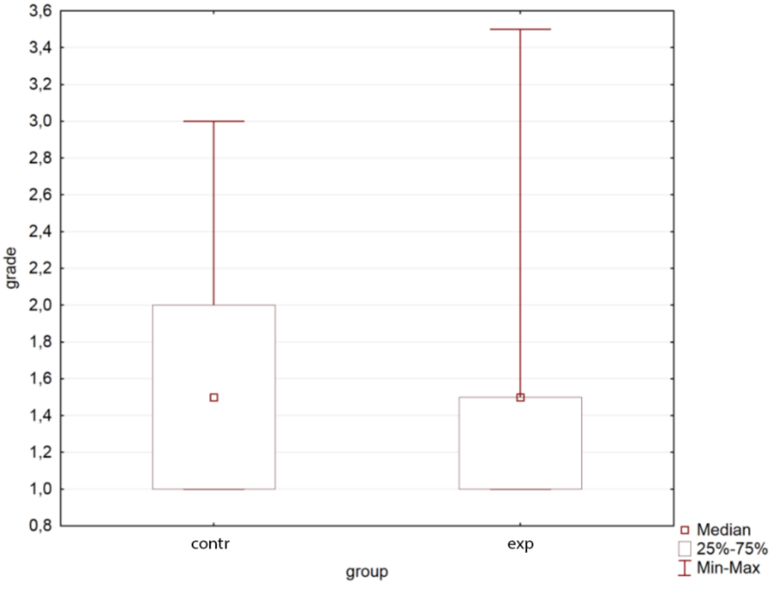

Figure 2: Visualization of achieved marks for the control and experimental group

Based on the results presented in Table 8, we do not reject the null hypothesis, i.e. the UT01 group, as well as the UT02 group, are equivalent in the level of achieved knowledge in the field of programming in PHP and JavaScript programming languages as well as theoretical knowledge in the field of web application development.

In our case, this means that both groups were equivalent before the intervention using the materials compiled by our methodology and the module we created. Based on the Kolmogorov-Smirnov two-sample test for posttest, statistically, significant differences are found, i.e. we reject the null hypothesis at the 5% significance level.

With the results (by rejecting the null hypothesis) we proved that the final results of groups UT01 and UT02 are different in the level of knowledge achieved in favour of group UT01, i.e. groups that used educational materials adapted using our methodology during the study, as well as a module for increasing attention during the study.

At the same time, we can observe an improvement in the overall results achieved by the students of the experimental group based on better values for the grade parameter. Based on the above results, we can say that experimental treatment in the form of formal optimization of educational materials in electronic form, as well as the application of defined stimuli when the specified time is exceeded during teaching, is didactically effective.

Discussion and Conclusion

The problem of the approach presented by us remains the teaching of more complicated educational units. In such a case, it is quite possible that, despite the great efforts of the teacher to simplify the substance in the educational materials, the limit will be exceeded. This fact has happened to us several times. Over time, students stopped perceiving the helper positively, but rather as an element that distracted them. As the main reason, students from the experimental group stated that if they saw the same graphic version of the helper 3 or 4 times in a row, they stopped paying attention to it, even though it always contained a different text. Thus, the students stopped paying attention to the very content of the help due to its, from their point of view, monotonous design.

We solved this problem by adding more graphical forms of helpers and selecting them at random. So, in addition to the auxiliary report, which was to enrich the student and show the issue a little differently, we also changed the graphic presentation. Thanks to this variation, the desired effect of changing the graphic stimulus were preserved, and thus increasing the student's attention during the study. As we mentioned, the way how we changed the graphical stimulus was based on random selection done by integrated function in PHP language (mt_rand). The only restriction to this selection was that the newly presented objected cannot be the one presented at the moment. This is not the most optimal approach because it might happen, although the probability is low, that the first occurrence of graphical helper might be the same as the third one, which would mean that the graphical variation of the helper would miss the desired effect. Based on this fact, one of the key elements that we want to focus in our future research is complex variation and also graphical personalization of each helper based on specific student behaviour.

Based on the analysis of experimental results, we can assume that there is only a slight difference in the applied methodology results for different lengths of educational materials. This was reflected in the fact that we did not notice a relationship between the number of views of the helper and the length of the study material. This finding can be interpreted as the fact that the length of the educational content did not play a role in the evaluation of the loss of attention while adhering to the formal rules of the presented methodology.

The main benefit of the article is the proposal of a methodology based on which it is possible to significantly improve the e-learning teaching process. Despite the fact that the presented methodology was developed on the basis of data from subjects focused on information technologies, we assume that its use is possible in multiple educational domains. The relevant methodology, in contrast to the methodologies we examined, can be very easily applied in the form of a computer program and thus, its usability in practice increases. At the same time, we implemented the relevant methodology in the form of a program module for the Moodle virtual education system. Thanks to the mentioned module, we were able to carry out an experiment, the results of which confirmed the positive didactic effect of the relevant methodology. With regard to our experiment, we can confirm that the methodology is applicable across known e-learning platforms.

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