

Assessing the Intensity of the Usability of the Course Content within the Virtual Learning Environment

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Abstract—Nowadays, education is a complex process that has many advantages. This is obviously proven, as there are high demands on skills in today's world. Therefore, it is a good approach to acquire this knowledge during the studies. Accordingly, there is a high requirement how to constantly improve and acquire new experiences. To meet as many of these parameters as possible, it is important that we have an appropriately structured environment for students. The teaching process can be interpreted in several ways. We focus on data analysis in the teaching process through e-learning systems. Obviously, these supporting systems have many advanced functionalities to make the entire learning process much easier to understand. In our work, we focus on methods and approaches by means of we can evaluate student behaviour and we can measure and evaluate the course settings. We used introductory programming courses for these measurement purposes. We explored various managerial settings inside a concrete course structure. Subsequently, we used statistical evaluation over the already cleaned and pre-processed data from the system. At the same time, based on these statistical confirmations, we can propose a set of methodological recommendations for the teacher, which will help us to improve the quality, feasibility of the entire teaching process.

Keywords—Activity evaluation, educational data mining, student behaviour, virtual learning environment.

1 Introduction

Nowadays e-learning is a constantly evolving area. We are dealing with an area which is extremely desirable, but not only in academic sphere but also in industry and other emerging sectors all around the world [1]. It is a form of education through which we can come to different kinds of information [50]. Nowadays, the e-learning is accessible from different devices, that makes this entire area more and more desirable [35]. The concept of lifelong learning is at the forefront and therefore the process of acquiring knowledge is very important [29]. The researchers described an appropriate usage of a support system is an essential approach how to facilitate and evaluate the accuracy of the entire learning process also by means of educational models [22] [28] [6]. The developed technology enhancements allow access to information from

anywhere and anytime. Due to this access we can measure and track the behaviour of students [40]. E-learning has many advantages that make it easier for the teacher to work throughout the teaching process [13]. As a result, learning becomes a managed and controlled process that is accessible to everyone, since e-learning is a widely used part of the learning process [45]. For that purpose, it is mainly referred to the web-based environment, which is nearly related to the web applications and technologies [14]. Their aim is to provide a course or a specific content, or educational materials to students, to allow a remote form of education and to provide the choice to manage the entire learning process [12].

As stated in [14] [12] as well-set electronic learning environment implies several functionalities, that will help in teaching to achieve the set goals. The author's recommendations and reasons to implement and use e-learning systems in education are as follows: explore the circumstances that in some way lead to success or failure of users in e-learning and in online courses examine the suitability of elements that are present in e-learning.

Our investigated research problem is to find out which activities are important for the reliable measurement of the course activities. For that purpose, we compared introductory programming courses from different academic years. We will establish our findings and stands over reliable data from the learning environment and examined courses, which we want to evaluate. We will apply statistical methods over these extracted and pre-processed data. Our goal is to compare the same course with various modifications in two different academic years. Our expectation is to get an overview over these two courses and its activities. We also expect that we could form some managerial suggestions as improvements for the teacher, which will be stated from the statistical results.

2 Related Work

The usability concept for a system has been described from various points of view [20] [49]. Thanks to [42] [23] the LA (Learning Analytics) is a rapidly emerging field. LA represents a concrete field which deals with the optimization of the learning environment to improve the whole teaching process [37]. An important goal of educational institutions is to timely identify the deficiency in students' knowledge [5]. Universities and educational institutions are successfully involved in this growing initiative. The demonstrable result is the knowledge and conclusion of students are statistically evaluated [18].

2.1 Learning analytics and course usability

According to [10] the LA field LA can also be used in other sectors than in teaching, but LA's goal is to support the learning process by identifying the behaviour of teachers and students in a virtual learning environment [10]. For this purpose, there is a high demand to choose the appropriate algorithms and procedure to analyse the student's behaviour [25]. Similarly, if a successful student gives a low performance in

the assignment or role or asks repeatedly for materials or procedures. The teacher can also determine how often has the concrete student accessed to these materials. This approach with the course usability was described by other researchers [52]. By means of the LA we can evaluate the quality and beneficial asset of different course components and sections [9] [46].

2.2 Course outcomes and course assessing

To assess the effectiveness of the learning process, it is important to mention the specific learning outcomes of courses, which are also referred to as course outcomes in the literature [51]. The outcomes of the courses can be defined as a form of a specific description of the student's knowledge acquired by the student after carrying out a certain course activity. Each output is scored according to the selected scale. Outcomes in Moodle help the teacher monitor progress with students. This approach allows us to analyse the student's activities [38] and state some recommendations for further purposes [44]. According to [19] course outcomes are a formal outcome of what students should achieve in a concrete given course. The outputs are a detailed knowledge, practical skills, creativity. In teaching and translating the whole course, the teacher expects, that students gradually acquire these expected outcomes [48].

3 Methodology

In our research we are dealing with a concrete introductory programming course. Introductory programming course represent the most important milestone in the education of students in computer science. Many students can get a job as a programmer [11]. Due to other methodologies a programming course is a very appropriate form, how to identify the suitability of the given course [47] [31]. We defined hypotheses in our research, which should be proven, over a statistical evaluation and interpretation of extracted data [3]. The course is divided into chapters, which are predetermined to explain the programming studies of students. These chapters include study materials, animations, graphic representations testing or other various activities [7]. Our methodology is based over statements of researchers, to reveal the rate of the course usage by students [41].

3.1 Introductory programming course as a source subject to the research

The aim of this introductory programming course is to inform students with the basic principles of programming. The prerequisite for the completion of the course is that students must acquire the basic knowledge and skills how to create a program and how to develop their own algorithmic thinking [32], by means of an appropriated engagement [34]. They must become more familiar with the principles of the object-oriented programming. We used an implemented introductory programming course [17] on portal: <https://edu.ukf.sk/>

The introductory programming course was divided into various sections and chapters [33], that follow each other and based on which students acquire basic programming and algorithmic thinking skills.

In our research we used the following methodologies:

- We defined the programming course and all its activities in separated years as subject for our research
- We stated H0 hypotheses for the examined variables in the courses
- We used exploratory analysis for the researched activities in the courses

To verify the stated hypothesis, we will proceed as follows:

- Data acquisition and preparation - pre-processing from the log file from Moodle, division of the retrieved data, creation of the groups etc.
- Data Analysis - the input data file contains data about the activities of 182 students in the course of Programming for two semesters. All activities from the introductory programming course at <https://edu.ukf.sk>.
- Descriptive approach – we provided descriptive statistics for each course activities about the students.
- Analytical approach – we can prove or reject the stated hypotheses by means of the evaluated data.

3.2 Programming course as a source subject to the research

The number and type of each individual activity, which are available for students in the Programming course is a prerequisite for the most accurate analysis and statistical evaluation. We classified students by means of the selected activities in the course. The Table 1 gives an overview of the frequency of each Moodle activity in the course.

Table 1. Count of individual activities in the course Programming different years

Type of the activity	2016	2017	2018
Assign	20	20	15
Book	9	9	9
Feedback	4	5	2
Forum	6	5	4
Label	27	32	39
Page	22	23	21
Quiz	16	24	15
Resource	68	60	64
URL	28	37	48
VPL	1	31	230
Sum	201	246	447

The entire teaching process is complex, and it continuously undergoes through various additional improvements. From the Table 1 is obvious, that the programming course is constantly being developed and modified.

3.3 Enrolled students in the programming course

Every year more and more students attend to the subject of programming (see Table 2). Students of applied informatics must pass through this subject obligatory. The main advantage of this course is to acquire the basic principles of programming and the algorithmic thinking knowledge of programming. This knowledge will help them solve other problems more effectively from other areas, such as. data analysis, computer networks, etc.

Table 2. Count of the enrolled students in the course in separated academic years

Year	The count of enrolled students in the course
2018	108
2017	82
2016	64

The student classifications are feasible, because it's based on the extracted data from the education system. According to [1] data extraction refers to the process by means of we can get relevant properties and behaviour of students [4]. We can obtain information to determine the behaviour of students in the learning environment, which will ultimately help us to identify the learning style. With these findings, we can provide the teacher with an overview of the students and the entire educational process. In the research [27] the author gives an opinion which learning styles are integrated in the electronically supported education. The basis of this research is demonstrably the level of available data. As more useful data is available to us, we can more accurately integrate these aspects of e-learning.

Through obtaining and cleaning this data, we can identify important information such as:

- The number of all students enrolled in the course
- Number of students' enrolments
- The number of clicks on each course material.

Based on this information, we can classify students who use the course working in it. By means of our described methodology and results interpretation we can improve the learning process. The types of the possible improvements are:

- Monitoring the performance of individual students
- Distribution of students according to their performance
- Identification of outliers, data for the early intervention of teacher
- Predicting the student's potential for all students to achieve optimal results
- Avoid the dropping in the course attendance
- Development of instructional techniques (e.g. course management)
- Analysis and evaluation of standard tools and methods
- Curriculum assessment

4 Results

Our main goal of the research was to create an overview supporting suggestions for teachers that will evaluate the intensity of the usability of course content. Based on the methodology we analysed the recorded student activity and the success of activities in the virtual learning environment [24]. In our results explorations we focused on the hypothesis's formulation in consideration of the defined research problem. The accuracy and quality of our research results depends on the number of analysed activities (Monsen, 2006), where decision trees were used as a method to identify important activities.

We investigated the data distribution and we assumed the certain relationships between variables. We compared mean and dispersion rates and examine time-dependent data.

4.1 Activities and student's evaluation in the course

From the teacher's point of view, we need to identify a student's transition through a specific course in a VLE environment [15]. We need to statistically verify whether the student's transition through the course meets our criteria.

The first phase of the experiment was to verify the comparability of students (over the years under review). The comparability of the groups was determined by a pre-test performed at the beginning of the semester. The knowledge of the students before the beginning of the programming course depended on the previous knowledge which was gained at the secondary school. Data was collected through an input questionnaire.

The questionnaire contained 39 items. The items were focused on areas such as: how the lessons were held in computer science, how many times a week student had a computer lesson, etc. This "result of self-assessment" of students was a pre-test variable that expresses the self-assessment of the knowledge level from computer science. From the obtained results we identified and compared the knowledge of students in individual years.

Primarily, the logging records from the Programming course were chosen for the realization of the experiment. The activities of the students were monitored during two semesters: winter semester 2017 and winter semester 2018. An important factor in the choice of the Programming for our experiment was, that the course went between these two semesters in years: 2017 and 2018 with a fundamental structure change as well as minor adjustments to the course content. Activities and teaching materials were rearranged in the course.

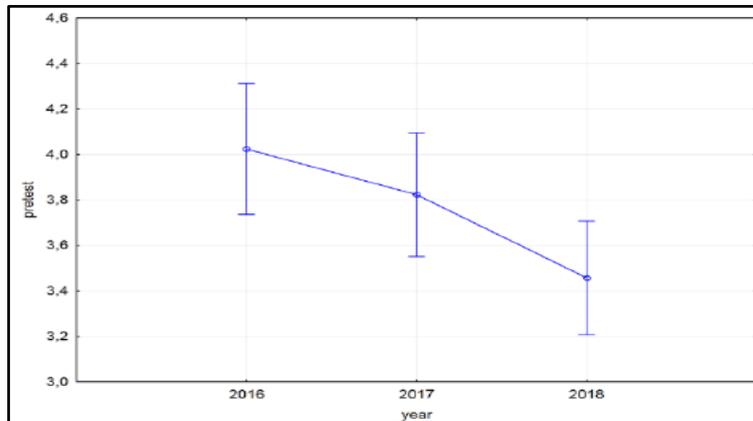


Fig. 1. Comparison of the pre-test scores in the surveyed years

After the comparison of the groups of students with statistically comparable results we obtained the data from the years 2017 and 2018.

4.2 Hypotheses formulation

Based on the result of analysis of variance, we reject the null hypothesis at the 5% significance level, which claims that results of the test do not depend on the year. We need to verify the validity of the following hypotheses:

- H0: There is no statistically significant difference in knowledge in the field between the control (2017) and the experimental (2018) groups
- H0: Activity in the course, in the "forum" section, does not depend on the course structure
- H0: Activity in the course, in the "file" section, does not depend on the course structure
- H0: Activity in the course, in the "page" section, does not depend on the course structure
- H0: Activity in the course, in the "URL" section, does not depend on the course structure
- H0: The variables which are describing the "file", "page", "URL" activities are independent in consideration of the course structure

The first hypothesis was verified above and confirmed the equivalence of both groups. Our goal is to reject the third, fourth and fifth hypotheses. By rejecting these hypotheses, alternative hypotheses come into force, claiming that activity in the course depends on changes in the course structure in section, forum, file, page, and URL.

The alternative hypothesis can be formulated as follows:

- H1: Provided activities by students in the programming course depends on the course structure, which is made by “file”, “page” and “URL” sections

In establishing these hypotheses, we described the variables, that we will analyze in our research.

4.3 Exploration of the evaluated records from course

By visualizing the distribution, we check the normality of all dependent variables: forum, page, file, URL. Based on the independent variable factor level in 2017 and 2018. We will verify this assumption by checking the categorized normal probability plot (see Table 3).

Table 3. Descriptive statistics for the investigated course activities

Level	Completely	Year	Year
		2017	2018
N	163	85	78
Forum mean	5.56	4.99	6.19
Forum standard deviation	6.02	5.52	6.51
Forum error	0.47	0.60	0.74
Forum -95.00%	4.63	3.80	4.72
Forum +95.00%	6.50	6.18	7.66
Book mean	9.99	11.54	8.31
Book standard deviation	12.18	14.04	9.56
Book error	0.95	1.52	1.08
Book -95.00%	8.11	8.51	6.15
Book +95.00%	11.88	14.57	10.46
Page mean	6.60	6.44	6.77
Page standard deviation	5.91	5.90	5.96
Page error	0.46	0.64	0.67
Page -95.00%	5.68	5.16	5.43
Page +95.00%	7.51	7.71	8.11
File mean	8.33	7.82	8.87
File standard deviation	6.09	5.97	6.21
File error	0.48	0.65	0.70
File -95.00%	7.38	6.53	7.47
File +95.00%	9.27	9.11	10.27
Test mean	117.25	123.00	110.97
Test standard deviation	54.67	52.84	56.27
Test error	4.28	5.73	6.37
Test -95.00%	108.79	111.60	98.29
Test +95.00%	125.70	134.40	123.66
URL mean	10.31	7.02	13.88
URL standard deviation	10.26	9.56	9.85
URL error	0.80	1.04	1.12
URL -95.00%	8.72	4.96	11.66
URL +95.00%	11.89	9.08	16.11

The table 3 contains descriptive statistics (mean, standard deviation, standard error, and 95% confidence interval for the mean) for the control and the experimental groups either in the years 2017 – 2018.

Table 4. Results of the analysis of variance for pretest

	df	pretest SS	pretest MS	pretest F	pretest p
Intercept	1	2704.599	2704.599	2270.227	0.0000***
Year	2	10.860	5.430	4.558	0.0117*
Error	190	226.353	1.191		
Total	192	237.213			

Note: * = $p < 0.05$; *** = $p < 0.001$

After the rejection of null hypothesis, we are interested in which years were statistically significant differences. Subsequently after a multiple comparison, we identified statistically significant differences between years 2016 and 2018.

Table 5. Multiple comparisons: Tukey test

	year	{1} 4.0238	{2} 3.8228	{3} 3.4572
{1} 4.0238	2016		0.5929	0.0166*
{2} 3.8228	2017	0.5929		0.1446
{3} 3.4572	2018	0.0166*	0.1446	

Note: * = $p < 0.05$

As a result of comparing students as shown in Table 5, the student groups in 2017 and 2018 are comparable. Comparability of student groups is also shown because of the Tukey test results.

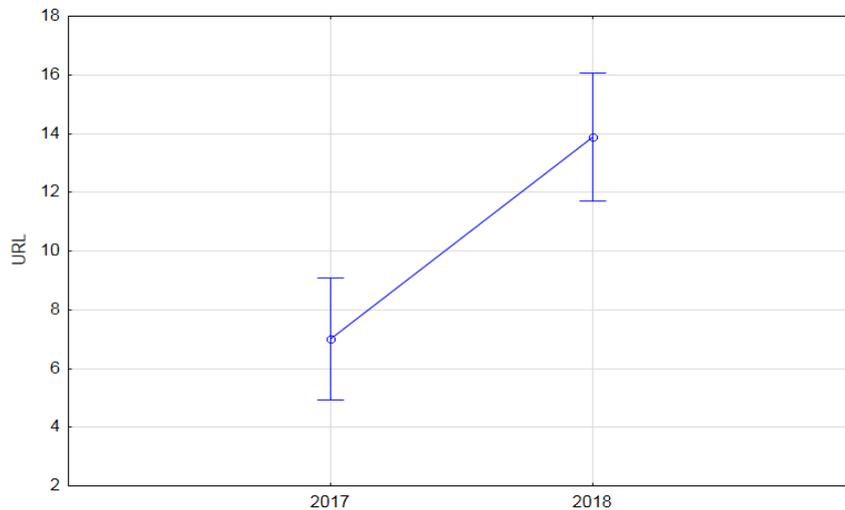


Fig. 2. Statistically significant differences in URL activities in given years

In the pre-experiment results we chose comparable groups, equivalent in the pre-test, whose knowledge levels were comparable, i.e. groups from 2017 and 2018. We compared exchange rate activities, that were the same and comparable in both years.

From the input data table, we obtained the following information, from which we created descriptive statistics. Through this approach we got the mean, standard deviation, standard error, and 95% confidence interval for the mean) for the control and the experimental groups either in the years 2017 – 2018.

The above described table contains descriptive statistics (mean, standard deviation, standard error, and 95% confidence interval for the mean) for the control and the experimental groups either in the years 2017 – 2018.

Table 6. Test of equality of variance

	Hartley F-max	Cochran C	Chi-square	df	p
Forum	1.3926	0.5820	2.1899	1	0.1389
Page	1.0197	0.5049	0.0076	1	0.9307
File	1.0794	0.5191	0.1166	1	0.7327
URL	1.0628	0.5152	0.0740	1	0.7856

Tests are statistically insignificant ($p > 0.05$), the equality of dispersion hypothesis was not rejected. It can be stated that the assumption was not violated, which was also confirmed by the non-parametric Levene’s test, given the identified deviations from normality.

Table 7. Nonparametric Levene’s test of homogeneity

	MS Effect	MS Error	F	p
Forum	69.4590	18.1643	3.8239	0.0523
Page	0.4393	14.7505	0.0298	0.8632
File	1.6354	14.0312	0.1166	0.7332
URL	10.6959	43.6152	0.2452	0.6211

After the verification of the introductory assumptions, the results of the variance analysis can be considered valid as follows. Significant value of F statistics leads to the rejection of the null hypothesis, so we reject H_0 only in case of URL, in the remaining three cases there were no statistically significant differences. The changes in the structure have no effect in activities like forum, page and file. In the URL section, we can confirm that the structure change had a statistically significant effect in this course.

Table 8. Analysis of variance for individual course activities

	Intercept	Year	Error	Total
df	1	1	161	162
Forum MS	5084.5410	58.9700	5821.1040	5880.0740
Forum MS	5084.5410	58.9700	36.1560	
Forum F	140.6281	1.6310		
Forum p	0.0000***	0.2034		
Page MS	7092.0450	4.5360	5658.7400	5663.2760
Page MS	7092.0450	4.5360	35.1470	
Page F	201.7798	0.1291		
Page p	0.0000***	0.7199		
File MS	11337.4600	44.7000	5965.0700	6009.7700
File MS	11337.4600	44.7000	37.0500	
File F	306.0032	1.2064		
File p	0.0000***	0.2737		
URL MS	17781.0300	1914.7500	15145.9100	17060.6600
URL MS	17781.0300	1914.7500	94.0700	
URL F	189.0111	20.3536		
URL p	0.0000***	0.0000***		

Note: *** = $p < 0.001$

5 Discussion

This study reveals the statistical analysis, that describes a complex view of the data to confirm or reject the stated hypotheses. We proved a set of suggestions in the teaching process of introductory programming courses [47] [21] [39].

We analysed significant activities through statistical evaluation [43]. The beneficial aspect is, that all these findings and reports can be easily interpreted and visualized [30]. We confirmed the key activities in the course, and we compared them in pursuance of the student’s activities and their knowledge in the specific virtual environment in higher education [26]. We compared the two groups of students if they are comparable. We tested the null hypotheses of collected and prepared data. It was set on statistical analysis [2]. We were relying on data analysis in the Moodle environment [16] [8].

Based on these exploratory analyses we can conclude that the managerial changes [36] in the course basically increased the visit rate on the selected activities, which helped the students to receive better evaluation results from the subject.

6 Conclusion and Future Work

The main aim of our research was to find out which activities of the training course are important for the final evaluation of students from the subject Programming and Data Structures. We added an approach to our solution for the course evaluation. Through this approach we identified whether the level of effort of students to attend

individual activities corresponds to the acquired knowledge and whether the resulting evaluation is reflected in these facts.

We clearly demonstrated statistically [8] significant differences in URL activities, which represented video tutorials about the basics of programming. This is very important because URL activities were references to introductory video tutorials. It is therefore clear that in 2018 students attended video tutorials more often. We found that the change in the course structure led to an increased interest of students in their studies. However, this is only demonstrable for URL activities. Conversely, a significant decrease was demonstrated in testing activities. The reason for the decline in testing activities was the transfer of students to VPL programming activities, where they were able to practice programming skills. The results of algorithms were automatically evaluated. The second reason was that test-type activities were voluntary for students during semester 2018 (i.e. they were understood as self-tests) and on the contrary they were mandatory in 2017.

In other activities statistically significant differences were not confirmed. This is also explained by the lower level of students' knowledge in 2018. Despite the findings of the test of comparability of groups, where statistically significant differences in the knowledge level of the groups studied were not confirmed, from descriptive statistics. We proved that the student's activities are emerged when we changed the course management. We can prove that the course management affects student activity in the given virtual learning environment, what is based on our previous findings. We proved our hypothesis in our research, which confirmed the importance of the establishment for a concrete analytical support for the teacher to make beneficial decisions.

This study like other researches already has limitations. A possible limitation is that the analysis was provided over introductory programming courses in various academic years from a single department with mainly the same curriculum.

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