Full research paper

IMPACT OF USING PERSONALIZED E-COURSE IN COMPUTER SCIENCE EDUCATION

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ABSTRACT

At current e-learning platforms, is often seen non-efficient usage of their possibilities when creating educational content. This article deals with the possibilities of using adaptive tools that are offered by learning management system (LMS) Moodle when creating a personalised e-course. The methodology created by the authors of the article for personalised e-course adjusts the study content based on characteristics of each student stated by his or her initial knowledge, learning style, and motivation. The article is aimed at the presentation of the created methodology and its impact on the level of student's output knowledge as well as overall learning efficiency. By using the methodology, there was an opportunity to compare the impact of two different approaches – the personalised one and non-personalised. Statistical analysis revealed that the use of personalized e-course has a positive impact on students' activity, motivation, and their level of output knowledge. The results showed that the attended secondary school has no or only minimal impact on the output knowledge if the students studied through the personalized e-course. An interesting finding was that students in all surveys have a stronger tendency to prefer the same learning styles over the years.

KEYWORDS

Adaptive approach, the effectiveness of education, e-learning, learning management system, Moodle, personalised e-course

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Highlights

- *A wanted grade from a subject affects the student's result from the final exam.*
- *Personalised e-course has a positive effect on the output knowledge of students.*
- *Using adaptive tools in e-learning raises motivation to study regularly.*
- *The majority of students from the research sample do not have a preferred learning style.*

INTRODUCTION

Improving ICT and their application affects sharing and transferring knowledge (Mudrychová et al., 2018). Today's students can study "anywhere and anytime". They use technologies not only for formal but also informal learning which they directly use in their study units at school or home using any device connected to the Internet. Using a virtual learning environment (VLE) affects planning, learning, proposing, checking, and assessing the educational process and providing educational content.

Collective education in a classroom or via standard e-learning is not able to react to the individual needs of students. Some students can get new information faster than this education form can do which leads to their dissatisfaction. On the other hand, for some, the pace is too fast and they cannot understand the problem to the needed extent. Students who are fine with the way of learning might not fancy the teaching method of a particular teacher. Later, these students might develop repulsion to the teacher and subject that he or she teaches which can lead to worse grades and results (Brusilovsky, 2003; Kostolányová, 2012; Magdin and Turčáni, 2015).

Mudrák, Turčáni and Burianová (2019) suggest solutions that lead to the personalisation of content in e-learning courses based on the characteristic classes of enrolled students. As for this issue, it is necessary to deal with forms of education that focus on the personality of the student and that are possible to use within blended learning as well as in distance learning with the e-learning support.

Personalised teaching or personalised educations mean that the student takes over the responsibility for his or her learning and adapts to possible changes. Personalisation reacts to the needs and interests of students and it also teaches them how to manage their learning – take over control and responsibility. It is not something that is done for them but something they take part in (Basye, 2018).

Personalised learning is often drafted through instruction methods that involve adaptive technologies intending to help all students achieve a high level of education, a so-called mastery (Basye, 2018). Mastery learning says that students cannot be divided into "good ones and bad ones" but it can be done only based on the pace of learning. The founder of the psychodidactic theory of Mastery learning, B. S. Bloom (1968), is convinced that if students have limitless time and optimally adapted learning, each student can learn the material on mastery level (it means 80-90% of the material).

Kostolányová and Šarmanová (2016) understand the term personalisation as an adaptation of solutions to various problems, situations, surrounding and other specific conditions and requirements of individuals. They also mention that when solving personalisation itself, these questions need to be answered: Who is it designed for? What is going to be adapted and in what way?

According to Despotović-Zrakić et al. (2012), each student is determined by a set of individual characteristics. These are expectations, motivation, learning habits and styles, needs, etc. Based on these attributes we can divide the students into individual characteristic groups.

Personalised learning based on Klašnja-Milićević et al. (2017) is an adaptation of methodology, syllabus, and educational environment in a way it will suit the needs and learning style of individual students. Moreover, the difference between regular e-learning, which takes students as a homogenous entity, and personalised e-learning is that the latter considers students as a heterogeneous mixture of individuals. Personalisation of e-learning can be seen as a process of deciding about the highest value for an individual from a set of possible choices. It can be implemented into a selected LMS by applying various adaptive criteria such as level of knowledge, motivation, study goals, and style of studying (Brusilovsky and Millán, 2007).

One of the personalisation techniques is the selection of appropriate learning content for a particular student or group of students (Caputi and Garrido, 2015; Perišić, Milovanović and Kazi, 2018). Another possibility mentioned by Kostolányová and Nedbalová (2014) is the division of students into different learning groups based on their level of knowledge and preferred sensory modality. The above-mentioned authors found out that this approach can bring many benefits to e-learning such as faster material grasping and long-term, higher quality memorizing of learned knowledge.

Based on the authors' findings dealing with the issue when creating the concept of personalisation of education, it is appropriate to use the solution via VLE, which has already been applied for a longer time.

There are 2 main forms of implementation presented. Some authors decided to create their own VLE based on their specific requirements such as the WELSA system (Popescu, 2010), TSAL (Hwang et al., 2008), DeLeS (Kinshuk et al., 2011), Protus 2.1 (Klašnja-Milićević et al., 2017) and more. The disadvantage of these systems is their focus on a particular educational purpose and therefore not having wider usage. On the other hand, there are those authors who chose using paid or open-source VLE, which allows the implementation of plug-ins or the possibility of editing the integrated modules.

The suitability of Moodle is shown by Despotović-Zrakić et al. (2012), who invented a method for creating adaptive educational courses for distance education in this LMS. The courses are organized and adjusted to 3 groups of students according to their learning styles. The authors use the Felder-Silverman learning styles model (FSLSM – see subchapter: Model of learning styles supporting personalisation of university education), while they leave out the sensing and intuitive dimension. They use only the pre-set functions of Moodle.

Based on research findings, Karagiannis and Satratzemi (2016) incline to implementation of adaptive techniques into Moodle rather than creating a new VLE. They suggest using an adaptation of the "hybrid dynamic user model", based on the knowledge and behaviour of users. They also use static user modelling based on the Index of Learning Styles (ILS) questionnaire (see subchapter: Model of learning styles supporting personalisation of university education) results and study goals. Obtained data are used to adjust the e-course at the beginning.

Gao et al. (2015) offer a solution of personalisation via the Particle Swarm Optimization algorithm. This algorithm was tested and applied in personalised e-course. The algorithm was simulated with 150 students divided into 5 capability levels. The other parameters of personalisation are: the difficulty of study materials, way of learning, expected study goals, and required time to read the study material.

Some limitations are named in Moodle by Caputi and Garrido (2015). One is no possibility to create complex relations between course activities and student profiles due to a lack of information in them. The next limitation is that it is not possible to make separate types of views of the e-course in a way that every student sees only his or her personalised content. To eliminate these flaws, they used standard functions of Moodle. To generate the ways in e-course they use automatic intelligent planners (LPG and SGPlan). To check the methodology, they use quantitative analysis of an artificially created sample of students and e-courses. As a second experiment, they created a qualitative evaluation aimed at educational content planning in which smaller groups of teachers and students took part.

Garrido, Morales and Serina (2016) suggest myPTutor, which uses planning techniques through artificial intelligence to create totally adapted educational ways as learning object sequences which meet with teachers' and students' requirements.

Zounek et al. (2016) make education via Moodle based on constructivist principles, project, and group education. The students themselves became creators of e-courses by which they adjust it and together with teachers make one working team. Teachers are in the role of tutors or couches of groups and give students feedback to their work.

Magdin and Turčáni (2015) edited the *Book* activity in Moodle which provides advanced adaptive behaviour of the previous module and named it "*Adaptive Book* ". The authors use the

ILS questionnaire to assign an appropriate learning style to each student.
Using adaptive mechanism implemented in Moodle which adjusts the educational content to qualities of students expressing their learning styles is presented by Perišić, Milovanović and Kazi (2018). The learning style of a student is dynamically determined by tracking activities of a student during the learning process and finding out behavioural patterns that describe each learning style. They use semantic web technologies. To research the effectivity of the created model, they verify the differences between experimental (personalised educational content) and control (standard e-course) groups.
Petri nets modelling is used by Kuchárik and Balogh (2019) to create e-courses for LMS. In the e-course, they use adaptive navigation using the completion tracking and access restriction tools. Based on the student's behaviour in the e-course and the use of Fuzzy logic, a prerequisite for his or her final evaluation is created.
Evaluating the effectiveness of the educational activities used is an important aspect of e-learning. One of the possibilities presented by Balogh and Kuchárik (2019) is the correlation between the final evaluation of students and the materials and activities visited in the e-course.
Nowadays there are ongoing efforts to suggest more effective conception possible to use in VLE. Authors of the article use integrated system tools that will identify the above-mentioned individual characteristics of students. From the findings we can learn that the more aspects are taken into consideration, the more precise personalisation of the study plan can be created.
The goal of the article is to verify the effect of the methodology created by us on the level of acquired study results in computer science education. We stated the main goal based on personal research in the selected area and from gained findings of the above-mentioned renowned authors' outputs. In the article, we present our results, which were calculated from a comparison of data from measures in the control and experimental group. The groups were formed from bachelor's degree students of the Department of Informatics (DI), Faculty of Natural Sciences (FNS) at Constantine the Philosopher University in Nitra (UKF). The created methodology was applied and verified in the teaching of the subject Logical Systems of Computers (LSC).
The article has the following structure. In the chapter Materials and Methods, one can find a presentation of the personalised e-course methodology. Next, there is the research methodology presented. The results of applied research are shown in the Results chapter. In the Discussion chapter, we evaluate the used methodology in computer science education at the 1st degree of university level. The Conclusion chapter summarises our findings, previous and future work.

MATERIALS AND METHODS

Model of learning styles supporting personalisation of university education

The selection of an appropriate LMS is only the first step in the successful personalisation of education. In fact, it is a quite complicated process. It is necessary to make a complex analysis from various aspects that affect the educational process. An important step is to focus on the personality of a student and, while creating the learning content, respect his or her individuality. Every student is strongly characterized by the way he or she studies.
There are many definitions of learning styles but widely accepted by theoreticians is the one from Keefe (1979: 2) as: 'Learning style is a combination of characteristic cognitive, affective and psychological factors that serve as stable indicators of how a student perceives, interacts and responds to the learning environment'.
Kaliská (2014) says that learning style is a biologically and developmentally determined set of predispositions that must be first identified by student or teacher and then encouraged, developed, and also controlled. Later she says that using learning strategies that respect the variety of learning styles positively affects the student's approach to learning.
Despite the different points of view and definitions of learning styles, we can say that the fundamental idea of learning styles is that each student has a certain style and prefers materials presented that way (Akbulut and Cardak, 2012).
There have been many theories in the area of learning styles models. In one of them, Coffield et al. (2004) identified 71 models of learning styles. They categorized 13 main models based on their theoretical importance in the field, extent of their use, and their effect on other models of learning styles.
One of the conceptions of learning styles that activates a wide variability of learning styles is Felder-Silverman's model of learning styles. The FSLSM is one of the last models of learning styles that were created in the environment of university education. Thanks to its strengths mentioned below it has become the most used model in the area of VLE. The advantage of this model compared to others is that R. Felder and L. Silverman describe learning styles in a more particular way, specifying the differences in learning based on 4 dimensions that reflect the typical learning behaviour (Kaliská, 2014; Karagiannis and Satratzemi, 2018).
The FSLSM consists of 4 dimensions based on:

1. processing information - *active* and *reflective* type,
2. type of information noticed by the student first – *sensing* and *intuitive* type,
3. preferred modality when presenting the material: *visual* and *verbal*,
4. way of solving problems – *sequential* or *global* approach.

Felder and Silverman complement their theoretical model with the possibility to identify the preferred styles of students via the ILS questionnaire and also offer exact manuals on how to create education that would come directly from students' needs preferring a particular learning style (Kaliská, 2014).
To identify the learning style, we will use the ILS questionnaire created by Felder and Soloman (2002). To designate a learning style, it is usually a long process that often needs using more diagnostic methods. The main advantage of using the ILS questionnaire is that it identifies the learning styles of students at the beginning of the term. It means it solves the time issue when diagnosing learning

styles. As Magdin and Turčáni (2015) put it, the ILS questionnaire provides a very exact quantitative estimate of students' preference for each dimension of FSLSM. The ILS questionnaire contains 44 items of dichotomic character, distributed in accordance with the four dimensions of learning styles of FSLSM where one option increases while the other decreases the score of each dimension (Magdin and Turčáni, 2015). The questionnaire evaluation is conducted based on the FSLSM – Figure 1.

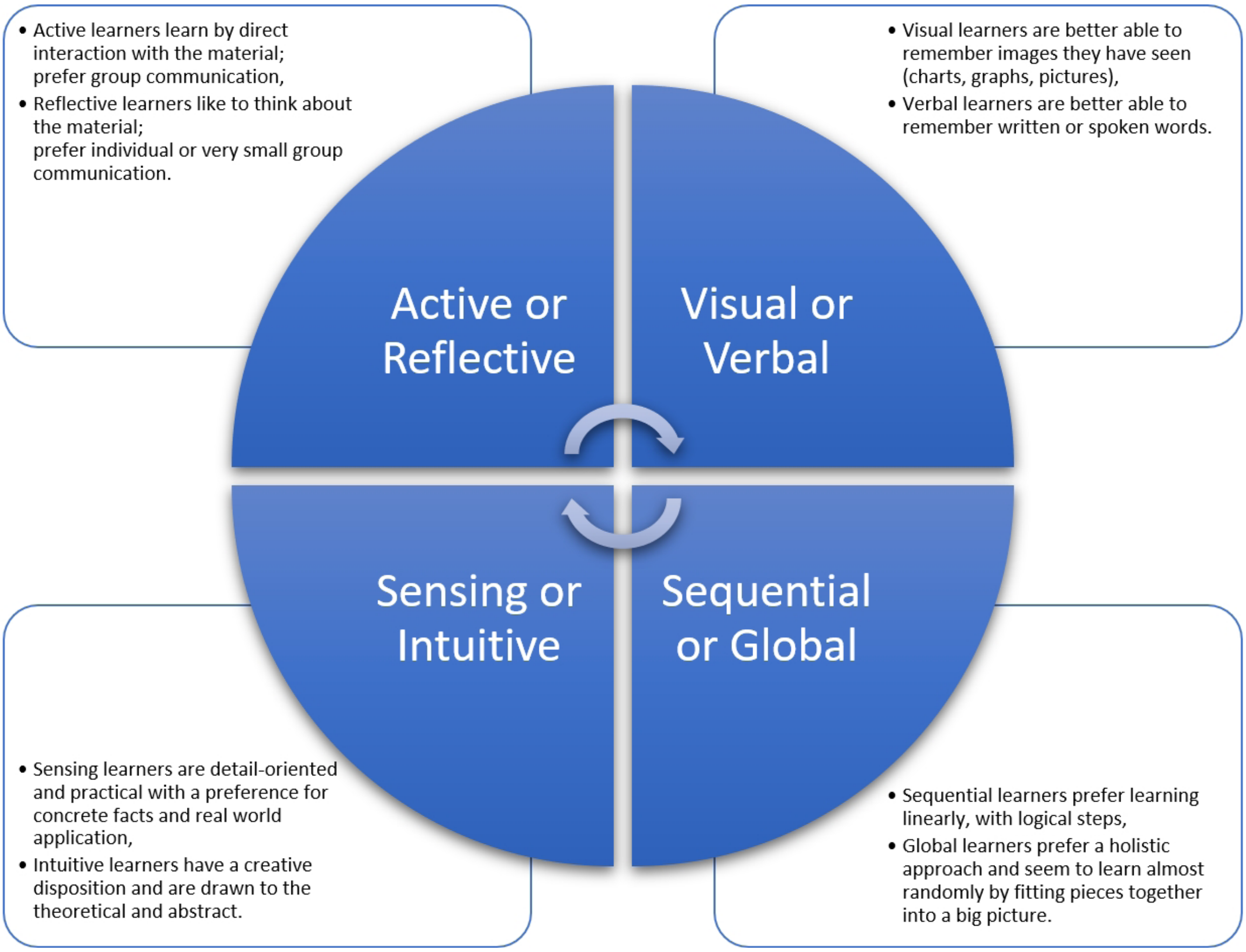

Figure 1: Felder-Silverman learning styles model, (source: Cater, 2011)

In the performed research, the ILS questionnaire was used for the experimental group.

As it was mentioned above, besides learning styles it is necessary to take into consideration some other characteristics too. For this purpose, we used a questionnaire as one of the tools of personalisation of education at the start of an e-course. To create the entry questionnaire that was applied at the LSC subject, the following steps were taken, described in Gavora (2010). It was a 10-item questionnaire with 5 open and 5 closed (3 dichotomous and 2 simple choices) items. The entry questionnaire was put together at the beginning of the e-course. This questionnaire aimed to get specific information about individual students such as motivation to study, information about previous studies, etc. Based on this information it was possible to create a student model before starting studying a subject. According to the student model, the e-course was adjusted to the student in advance to suit his or her needs the most. After this phase of preparing a personalised e-course, the following very important phase is tracking student activities in VLE in real time. The system saves these data about the student to its database. After evaluation, it adapts its content, appearance, etc. to the particular student. By Karagiannis and Satratzemi (2016), better results are achieved in the second phase of tracking and evaluating the activities, in a so-called dynamic approach, because in the first, static approach, we operate only with the initial state of information about the students and not specific state as in this dynamic approach.

Based on the above-mentioned information and results from the previous research seen in Mudrák (2018) a solution was prepared with a combination of these approaches. With the static approach, we can find out information via diagnostic methods that we could hardly get from student's activities in the e-course. It then helps to adapt the e-course to new students at the beginning. With enough data about each student, it is more appropriate to do more adaptations with a dynamic approach.

The principle of a dynamic approach is personalized feedback. It consists in generating the study material or its part based on the test result, the form of which is specified according to the chosen approach to the student. Students are divided into groups for this purpose. Depending on the group in which the student is included and his/her activities in the e-course, the student is automatically allowed or denied access to various parts of the e-course. The dynamic approach was also applied by using activity tracking and access restriction tools in Moodle.

The methodology of a personalized e-course

The authors of the article created an e-course with attributes of personalisation, which they implemented into LMS and it meets the requirements given by Paramythis and Loidl-Reisinger (2004). Based on a survey they conducted, a personalised educational system (personalised e-course) meets the following requirements:

- monitors activities of its users,
- interprets their activities by specific domain models,
- deduces requirements and preferences of users from their activities,
- appropriately represents them via connected user modules,
- appropriately reacts based on available information about its users to dynamically make the learning process easier.

From these defined requirements, it was necessary to analyse and identify the flaws of currently used e-courses in LSC subject.

LSC is a subject for first-year students at the Applied Informatics study program (AI) realized during the winter term by blended-learning form. In addition to the e-course, there are seminars and lectures provided to students weekly (11 weeks in total). This subject is focusing on the area of logic circuits, their functionality, division, and on solving tasks in a field of analysis and synthesis of logic systems. An elaborated didactical e-course with study content is available for students in the form of multimedia. The e-course content is divided into study units according to weeks in the term. It means 11 units overall. There are an introduction unit, 9 topics units (lessons), and a final unit. The introduction unit contains general information about the successful passing of the subject, *Forum*, *Feedbacks*, *Workbook*, and the pre-test (described below), etc. Every topic unit contains the introduction and edited *Book* activity consisting of text, pictures, and interactive animations (5-20 pages of the theoretical curriculum). The material is extended by external sources such as videos and websites. The output of each topic unit is a *Quiz* activity for classical teaching (Autotest – 10 questions from the new curriculum). In the case of the personalised e-course, the *Quiz* activity contains personalised feedback (Revision – 10 questions from the new curriculum plus 2 random questions from each completed topic unit).

This results in the following structure of every topic unit:

- Introduction to the unit,
- edited *Book* activity,
- other sources (websites, pdfs, videos, docs),
- *Assignment*,
- Revision (Autotest for classical teaching).

Moreover, adaptive navigation was created based on learning styles and the current knowledge of experimental group students. The final unit contains the evaluation questionnaire (only for the experimental group of students) and the post-test same for all students, which is also the credit exam. The credit exam (post-test) consists of 38 questions (answer types: 33 multiple-choice, 3 short texts, and 2 numerical) which are the same for all students. Students must complete the credit exam to take the final exam. The LSC course is ended by a written final exam, which consists of 4 questions. The first two questions are focused on the ability to draw circuit diagrams and perform analysis, and synthesis of logic circuits. The remaining 2 are randomly selected theoretical questions. Each question is evaluated by a grade and a final grade is calculated as the arithmetic mean of these grades.

The implementation of the correct LMS methodology for its users, according to Balogh and Koprda (2014), means that there is a detailed model that covers all aspects of the system. The authors have created the universal model of the student's e-course transition in LMS determined by using Petri Nets. Some parts of their model were followed by developing the methodology described below.

After the ILS questionnaire (described in more detail in the chapter Research methodology) evaluation by the experimental group of students, they were assigned into two sub-groups within the e-course according to the way of grasping learning material either globally or sequentially. Passing the e-course by students of the two groups were different:

- For the sequential group (58 of all records; 27 of the cleaned records) in order to access the *Quiz* activity, he or she is supposed to study the content of these activities containing the study material (*Book, Adaptive Lesson, external resources*, etc.). The *Quiz* activity was chosen as the main checkpoint of each unit to verify student knowledge and provide personalised feedback (Mudrák, Turčáni and Burianová, 2018). In case of a sufficient number of correct answers (corresponding to the chosen level of mastery learning in the *Quiz* activity - 80%), the sequential student gets access to the next unit. If the student does not reach a sufficient percentage, after completing the *Quiz* activity he or she can learn about his or her mistakes via results in personalised feedback. After evaluation of the knowledge test of the selected unit, the system will refer the student to a specific place in the e-course, or to external sources, where all the information about that issue is located. It is only after re-studying the problematic issue that the student can take the *Quiz* activity again. In order to maximize the reliability of the *Quiz* activity, its content is limited by time, with the possibility of generating questions, selecting from a file, and also limited by the number of attempts. The content of the *Quiz* activity also takes into account the pedagogical-psychological principles of forgetting. As the student progresses through the e-course, the *Quiz* activity contains randomly generated questions from previous units, which support the systematic repetition of the already learned material. If the student fails in the *Quiz* activity more than twice, he or she is advised to consult a teacher personally using the interview method, to find out the reason for the failure. Based on the consultation, the teacher/tutor will modify the study recommendations for the student to eliminate failure in the next lessons.

- In the global group (36 of all records; 17 of the cleaned records) do not use conditioned access to each unit but have access to the entire content of the e-course. The teacher/tutor wants them to fulfil the appointed activities by a particular date and time.

The model on which the methodology of passing the course by the experimental group students is based is shown in Figure 2.

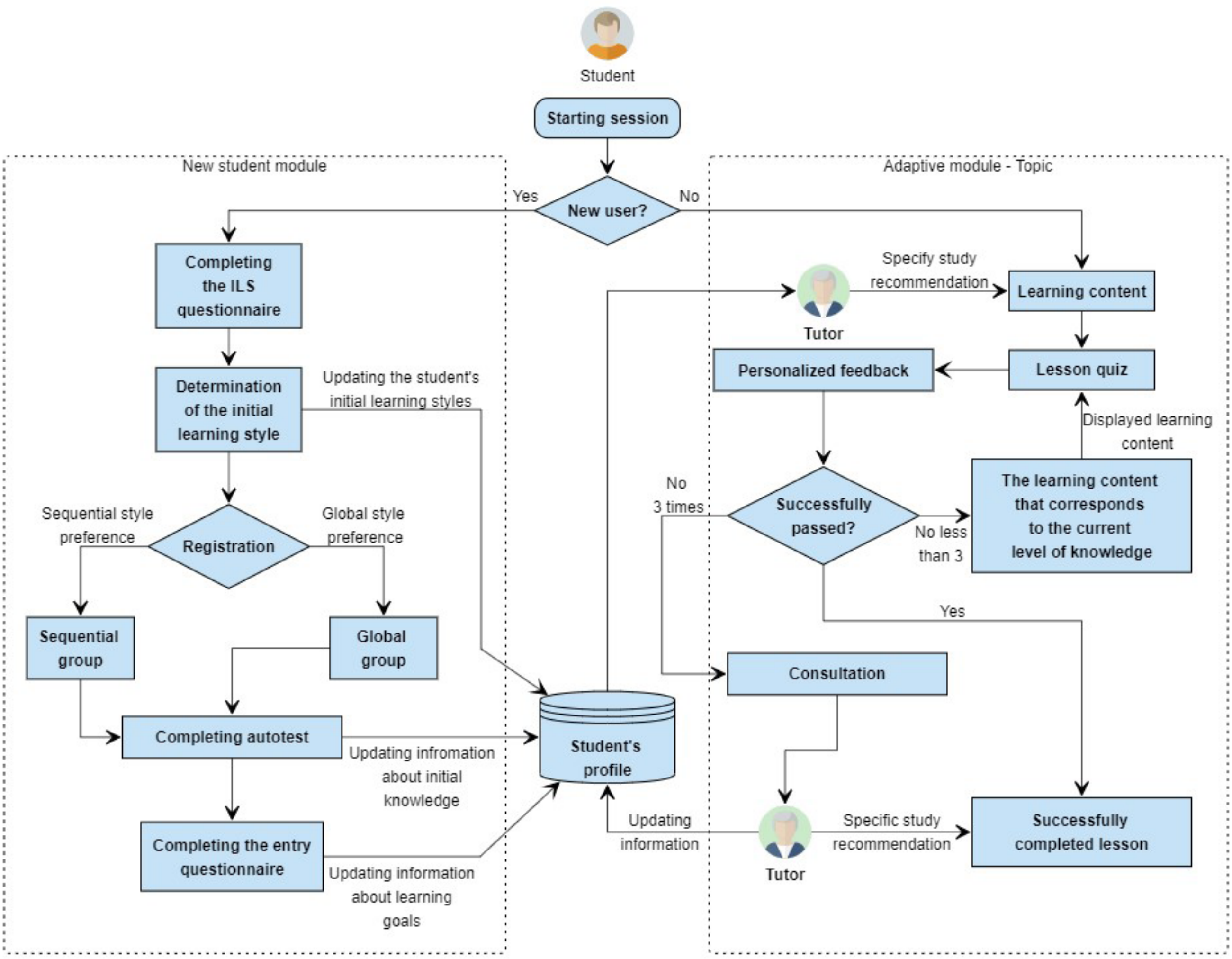

Figure 2: Passing the e-course by experimental group students, (source: own design)

The control group students have the same study material as the experimental group of students. However, at the beginning of the term, their learning style was not discovered. It follows that there is not recommended the most appropriate study content for students' learning styles, in this case. Course activities are not conditioned for students in the control group and all units are open for them throughout the term. Instead of customized *Quiz* activity, they use activity *Autotest* without personalised feedback. However, the test questions are the same, generating questions from previous units is not used and the correct answer is given immediately after completing the *Quiz* as student's feedback. Students of both groups have the same conditions for completing the subject.
After its evaluation students of EXP group were assigned into two sub-groups according to the way of grasping learning material either globally (EXP_G) or sequentially (EXP_S). This division was created only for the methodological point of view. The use of the ILS questionnaire is described in more detail in the chapter Research methodology.

Research methodology

These research questions were stated by us:

Q1. What is the level of initial knowledge of new students of DI?

Q2. Does the type of previous secondary school affect the output knowledge of students?

Q3. What level of study motivation do the new students possess?

Q4. How does the created methodology affect the quality of output knowledge?
Q5. What learning styles have new students at DI?
Q6. What impact has the used methodology on the learning activity of students?

In order to obtain relevant answers to some research questions and their qualitative evaluation, the following research hypotheses were stated by us:

H(1a): There is no statistically significant difference in input knowledge between groups of students from different types of schools.
H(1b): Initial knowledge of students experimental and control group from LSC subject is at the same level.
H(2): There is no statistically significant difference in output knowledge between the EXP_TS and EXP_OS group.
H(3): A wanted grade from the subject affects the results of students from exams.
H(4): There is no statistically significant difference in output knowledge between the control and experimental group students.

All students received questionnaires and a pre-test at the initial lesson. The *Feedback* activity was used to create the entry questionnaire (described in chapter: Model of learning styles supporting personalisation of university education) in Moodle.
Students in the experimental group filled in the ILS questionnaire and the results were interpreted in e-course via the *Feedback* activity too. A standardized questionnaire was selected because of its reliability, simplicity, and free availability on www.webtools.ncsu.edu/learningstyles/.
ILS questionnaire aimed to identify the learning styles of students. There were recommended individual study way and learning activities to students which correlate the most with their learning style according to the ILS results. This was followed by enrolment in the course and a pre-test. The pre-test was carried out in the form of a *Quiz* activity and it contained 13 questions, 11 of which were Multiple-choice type and 2 Numerical-answer type. The pre-test aimed to find out information about the students entering the course, concentrating on their initial knowledge. The pre-test does not count into the final grade, but it has to be passed by students to unlock study content.
With students of the experimental group, it was tried to use the possibilities of Moodle such as conditioned access, fulfilling activities, gamification (Level up!). Besides, personalised feedback was created through *Lesson* and *Quiz* activities for learning management.
Based on the above-mentioned research methodology, necessary research files were created to verify the presumptions. To test hypotheses and answer research questions concerning differences in knowledge between different groups of students (hypotheses H(1a), H(1b), H(2), H(4), research questions Q1, Q2, Q4), the *t*-test was used for two independent variables (Munk, 2011) and formula (1) was applied:

$$T = \frac{\bar{x} - \bar{y} - (\mu_1 - \mu_2)}{\sqrt{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}} * \sqrt{\frac{n_1 n_2 (n_1 + n_2 - 2)}{n_1 + n_2}} \qquad (1)$$

Where μ_1, μ_2 are the mean values of the variables being compared and s_1^2, s_2^2 are the variances of the variables.
The statistical dependence between the wanted grade and the real final exam result of the LSC subject (hypothesis H(3)) was examined by means of the correlation analysis (Munk, 2011) with the application of the formula (2) for calculation of the correlation coefficient:

$$\rho_{XY} = \frac{\sigma_{XY}}{\sqrt{\sigma_X^2 \sigma_Y^2}} \qquad (2)$$

The significance level for testing the hypotheses was chosen to be $\alpha = 0.05$.
The reliability of the evaluation questionnaire was calculated by using Cohen's kappa coefficient (Chráska, 2016). The formulas (3) and (4) were used for this purpose.

$$\kappa = \frac{p_p - p_o}{1 - p_o} \qquad (3)$$

where

$$p_p = \frac{1}{n}\sum n_s \text{ and } p_o = \frac{1}{n^2}\sum n_I * n_{II} \qquad (4)$$

The application of Cohen´s kappa coefficient κ assumes a random division of respondents into two groups of the equal size. The meaning of variables in formulas (3) and (4) is:

κ - Cohen's kappa coefficient for one questionnaire item
p_p - the observed proportion of agreement
p_o - the expected proportion of agreement (the overall probability that the respondents would randomly agree)
n_s - number of identical answers for each variant of the questionnaire item in both groups of respondents
n - total number of answers to the questionnaire question
n_I, n_{II} - number of answers for each variant of the questionnaire item in the first and in the second group of respondents

For the purpose of calculating the reliability of the evaluation questionnaire, we divided students of the experimental group into two random groups of the equal size. Then for the individual questions of the evaluation questionnaire, matrices capturing the agreement of the answers were created and reliability values were calculated. The average value was obtained from the measured reliability values (the calculated reliability is stated in chapter Results).
Statistical software STATISTICA, version 7.0 was used for calculations.

Research sample

The research sample was a group of first-year students of AI studying at UKF in Nitra. One experimental and one control group was created. Students in the control group had unlimited access to all educational material during the term and studied based on the original methodology using the basic e-course.

Students in the experimental group studied via the created personalized e-course based on the created methodology.
Raw research sample before removing inconsistent records was made of 114 students. The students were divided as follows:

- 20 control group students,
- 94 experimental group students.

A selection of compact groups was used, which were created using data recorded in the Academic Information System (AIS) database. Only records of students whose data were complete were used in the final research sample. The complexity of the data needed to test the individual hypotheses was also distinguished separately. This means that the final research sample did not contain, for example, records of students who passed the post-test but for some reason did not solve the pre-test and other similar cases. However, if they completed the ILS questionnaire at the beginning of the semester, these records could also be used for some analyses.
The data return for the pre-test and post-test was 51.75% (59 students, who have passed both pre-test and post-test). This sample was used for hypotheses testing.
Based on the above-mentioned parameters, the following groups were created to test the hypothesis:

- CON – control group students who have completed all the necessary activities,
- EXP – experimental group students who have completed all the necessary activities.

The division into CON and EXP groups was used to test hypothesis H(4), which belongs to the research question Q4. A more specific division of these groups was needed to verify further research questions. This was done based on the way the course was completed. To test hypothesis H(2), which belongs to the research question Q2, it was necessary to divide the EXP group in another way. In the case of attended secondary school, we divided the EXP group of students into two subgroups:

- EXP_TS group, which included all students with finished technical secondary schools,
- EXP_OS group, which consisted of students from other schools.

The composition of each group is shown in Table 1. Experimental and Control group are the numbers of all students who participated in the LSC course. The Final research sample is a sample of students/records that contained all the results needed to evaluate the research hypotheses (pre-test and post-test score; in the case of the Experimental group also the result of the ILS questionnaire). The CON group is thus a subset of the Control group and Final research sample records. The EXP group is a subset of the Experimental group and Final research sample records. The EXP_TS and EXP_OS groups were created by splitting the EXP group records based on whether or not the student attended a technical secondary school. Part of the analysis was created according to questionnaires results, where took a part 94 students of the experimental group.

Group	Students
All students of the subject LSC	114
Experimental group (raw)	94
Control group (raw)	20
Final research sample	59
EXP	44
EXP_TS	15
EXP_OS	29
CON	15

Table 1: Number of students of each group, 2019 (source: own calculation)

RESULTS

Hypothesis H(1a) is based on the presumption that there are students accepted to the FNS of the UKF from secondary schools with a different focus. As some of the students addressed the basics of the subject matter, which is already linked to the content of the LSC subject at secondary school, it was assumed that they would perform better in the pre-test than students who had come from other secondary schools. The results of the measurements are shown in Table 2.

Variable	Average EXP_OS	Average EXP_TS	*p*-value
Pre-test (percentage)	61.15	79.49	0.004

Table 2: Comparison of pre-test results based on the type of secondary school (*t*-test for two independent variables), (source: own calculation)

Based on the *t*-test results, a statistically significant difference was found between the EXP_TS and EXP_OS groups in the pre-test results. In particular, the EXP_TS performed better after the pre-test than the EXP_OS group.
The *t*-test method was also used for the hypothesis H(2) testing. There were compared post-test results for the EXP_TS and EXP_OS groups. The results are shown in Table 3.

Variable	Average EXP_OS	Average EXP_TS	*p*-value
Post-test (percentage)	78.95	80.66	0.742

Table 3: Comparison of post-test results based on the type of secondary school (*t*-test for two independent variables), (source: own calculation)

The data in Table 2 and Table 3 suggest that although there was a statistically significant difference in initial knowledge between the EXP_TS and EXP_OS groups, these differences were balanced out at the end of the term. After the post-test, it showed that there was no significant difference in output knowledge between these groups.
The purpose of the further analysis was to test hypothesis H(3), which is based on Q3. The motivation of a particular LSC student was assessed by the answers in the entry questionnaire. The questionnaire contained the question: “What grade would you like to get from the LSC course?” We assumed that if students stated that they wanted a better grade, they were

motivated to develop in this area. If they answered that would be fine with a worse grade, they probably did not care about this issue and were, therefore, less motivated. Based on these presumptions, hypothesis H(3) was stated. The results of the correlation analysis of the dependence between the wanted grade and the exam results are shown in Table 4.

Variable	Exam
Wanted grade	0.4422
	$p < 0.001$

Table 4: Correlation analysis of dependence between the wanted grade and the exam results, 2019 (source: own calculation)

The results of the correlation analysis indicate that there is a statistically significant dependence between what grade the students wanted at the beginning of the semester and the result of the exam.

The main objective of the research was to verify whether the methodology used for teaching through a personalised e-course is more effective than a traditional e-course. To investigate this problem, there were formulated hypotheses H(1b) and H(4) and tested by experiment. The post-test results of the CON and EXP group were considered to be decisive in verifying the output knowledge. However, it was necessary to verify that the initial knowledge of the students in both groups was the same. Therefore, a *t*-test for two independent samples was used to compare the pre-test results of the EXP and CON group. The calculated results are shown in Table 5.

Variable	Average EXP	Average CON	*p*-value
Pre-test (percentage)	57.59	80.28	$p < 0.001$

Table 5: Comparison of results from pre-test for the EXP and CON group (*t*-test for two independent variables), (source: own calculation)

Based on the results in Table 5, we can see that the groups are not equal. Therefore, it was not possible to compare the results of the EXP group and the CON group only based on the results from the post-test but it was necessary to calculate the difference score. This value is obtained by calculating the difference between the score obtained in the pre-test and the post-test. By this difference score, which is a form of expressing student progress, we can verify how much the students in the groups have improved. To illustrate, the result of calculating the difference score is also shown in Figure 3 using a box graph.

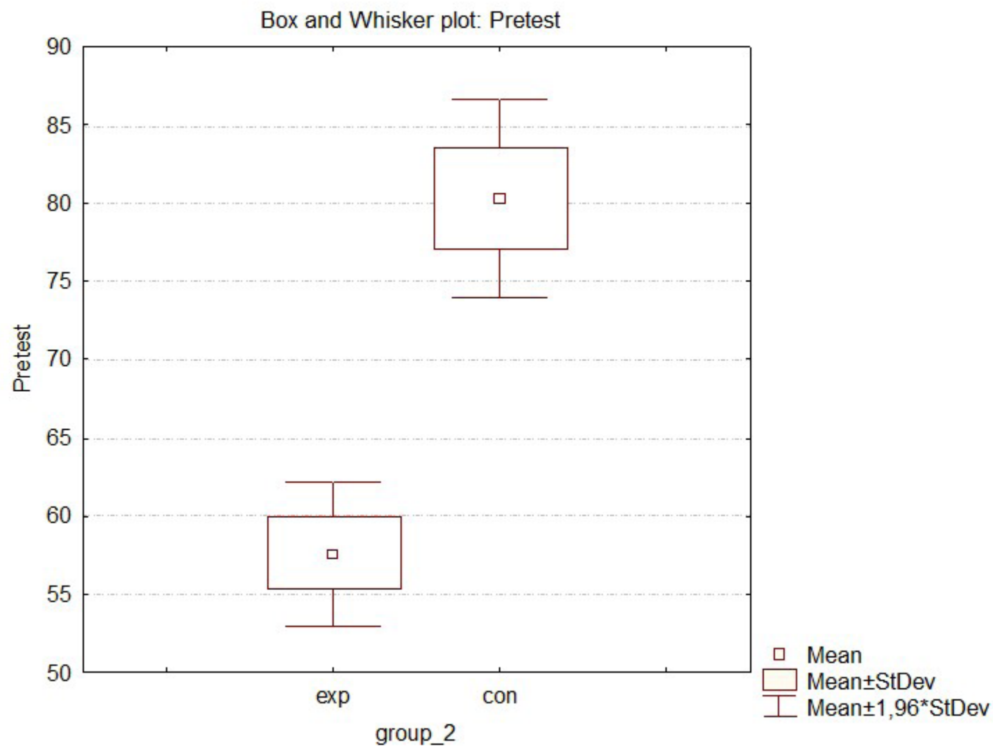

Figure 3: Results of a pre-test for the EXP and CON group, (source: own calculation)

After calculating the difference score, the presumption expressed in H(4) could be tested. The results in Table 6 and Figure 4 show that there is a statistically significant difference between the EXP and CON group differential scores.

Variable	Average EXP	Average CON	*p*-value
Dif_score (percentage)	26.54	-13.87	$p < 0.001$

Table 6: Comparison of difference score of post-test for EXP and CON group (*t*-test for two independent variables), 2019 (source: own calculation)

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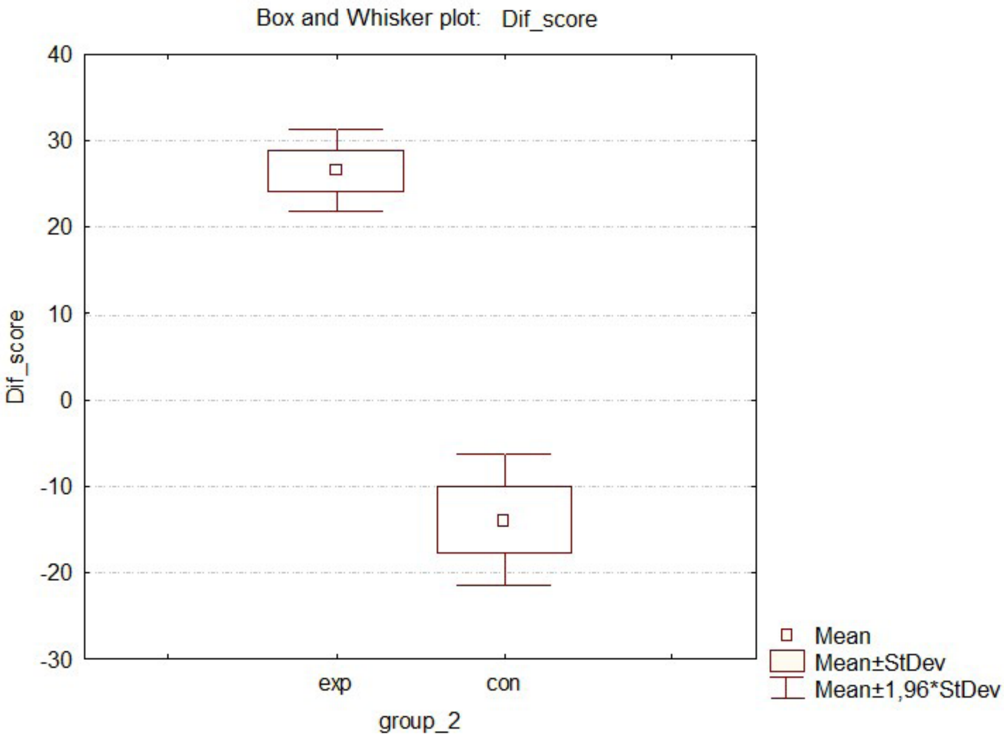

Figure 4: Difference score of post-test for EXP and CON group, (source: own calculation)

Based on the above, it can be concluded that visibly better results were confirmed in the evaluation of the output knowledge of the EXP group compared to the CON group.

An important factor was to determine the extent to which the students' learning styles affect them. According to the FSLSM, students were divided into 3 categories: balanced (lowest impact, ILS result value between 1-3), moderate (ILS result value between 5-7), strong (ILS result value between 9-11) (Mironova et al., 2013; Grzybowski and Demel, 2015). The arrangement of the categories is shown in Figure 5. From Figure 5 it is clear that more than half of the students (54%) do not incline to any particular learning style within the FSLSM. Furthermore, 35% of students have moderate preferences for at least one learning style and only 11% of students have strong preferences for at least one of the learning styles.

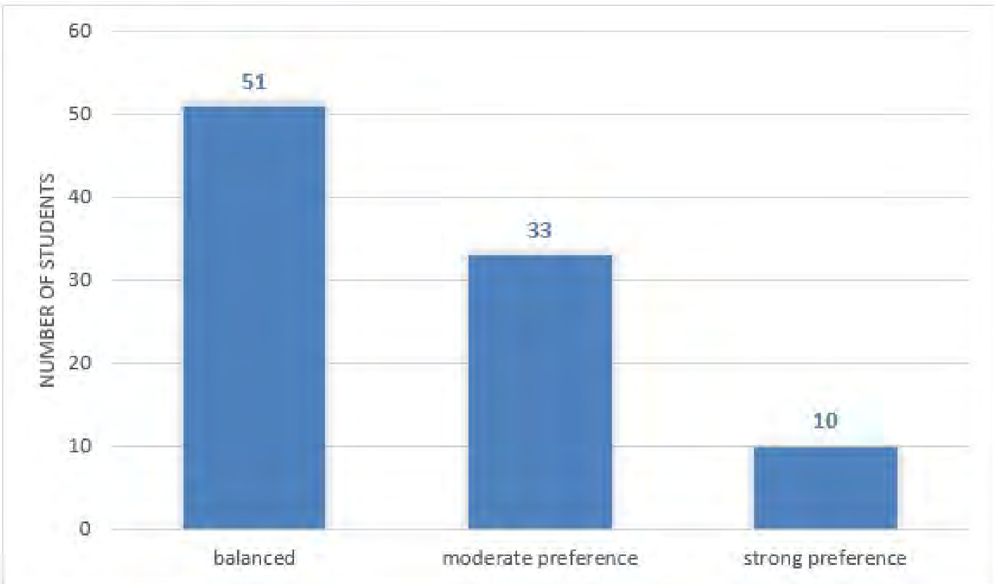

Figure 5: Arrangement of students based on the extent of the impact of learning styles preference, 2019 (source: own calculation)

For each category, the count of students for each learning style listed in Figure 6 was also evaluated. For the Balanced and Moderate categories, there is a representation of each of the FSLSM styles. However, the Balanced category is not really significant in terms of particular learning styles, as the learning styles contained in this category do not significantly affect the student's learning style. More interesting were the results of the Moderate category, where the largest representations of learning styles were Visual, Sensing, and Active. In the Strong preferences category, the most notable learning styles were Sensing and Visual.

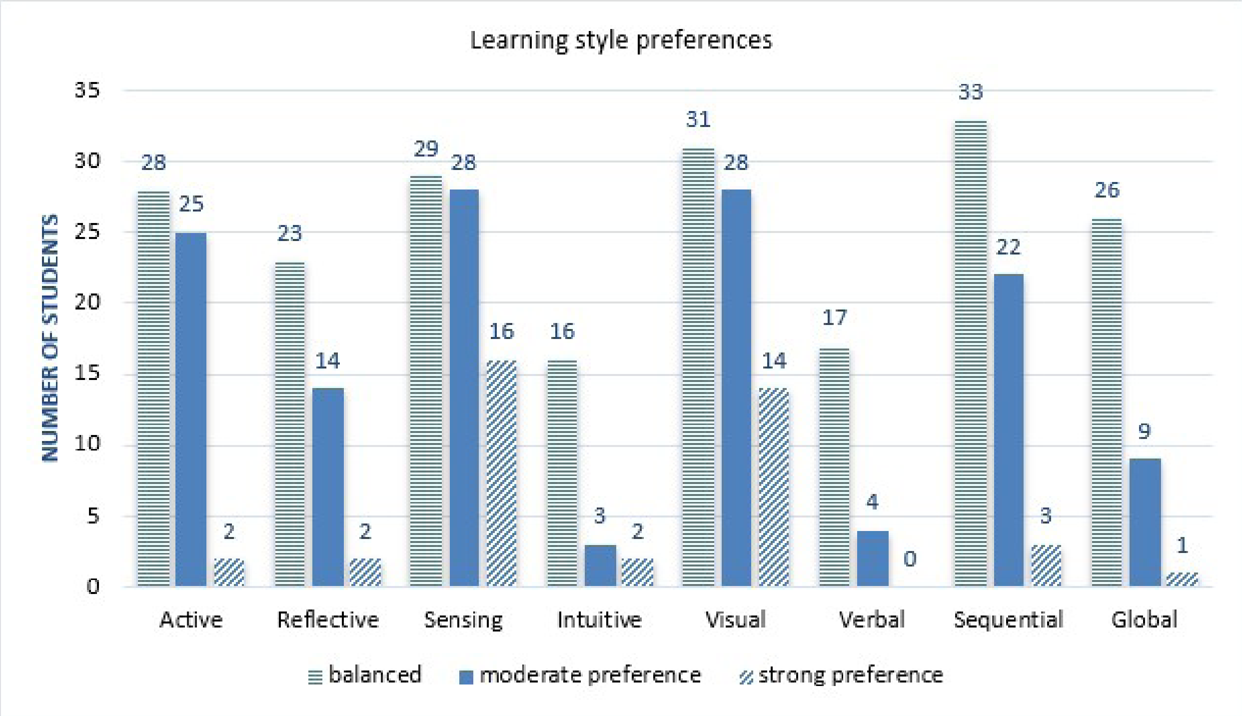

Figure 6: Representation of learning styles in each FSLSM category, (source: own calculation)

Based on the above mentioned and summary of our experience it was evaluated the obtained results as quite logical for the studied subject of the AI. In general, this means that AI students prefer mainly materials processed in graphic form (images, animations, videos, etc.), they like to work actively with the given study content and for their study, it is appropriate to engage as many senses as possible. So, they are more practical. Concerning the continuity of the materials, they prefer a sequential approach, so they prefer to synthesize and prefer a logical continuity of materials.

For the answer of Q6, it was important to find out the impact of the described methodology on student activity in the personalised e-course. The task of the proposed methodology was to use such tools that would motivate students to study at regular intervals and voluntarily, without any external influences such as credits and so on. Via adaptive tools provided by Moodle, in addition to the personalisation of learning content, the intention is also to motivate students to study regularly. Moreover, there was an effort to eliminate students' procrastination during the term, which could positively affect the study effectivity, level of knowledge, and reduction of the stress factor before exams.

One of the problems of the original e-course, which was created classically, was that students accessed the e-course only before the exam. Using the *Reports* analysis tool in Moodle, the student activity was evaluated and compared during the winter terms 2016 to 2018. This activity is shown in Figure 7 and Figure 8.

In 2016, the education was done through the original e-course (99 students). In 2017, the research was launched, and the first changes were made in the e-course (the e-course was attended by 107 students). Based on the findings in 2016 and 2017, the e-course was adjusted using the methodology described in this article. From Figure 7 and Figure 8 a significant increase in the activity of experimental group students (research sample of 94 students) in the e-course is observed.

To avoid basing data only on logs obtained from Moodle, the evaluation questionnaire was used at the end of the term. Students of the experimental group evaluated the impact of the applied methodology on their motivation to study on a scale from 1 - no impact to 5 - significant impact.

Research also showed that 60.65% of students evaluated that the methodology used had an impact on their motivation to study and 25% had a neutral attitude. Only 14.35% of students were in favour of the possibility that the methodology used did not affect their motivation to study.

The reliability of the evaluation questionnaire result is given by Cohen's kappa coefficient $\kappa = 0.812$. According to Chráska (2016), the calculated value of κ can be considered as satisfactory.

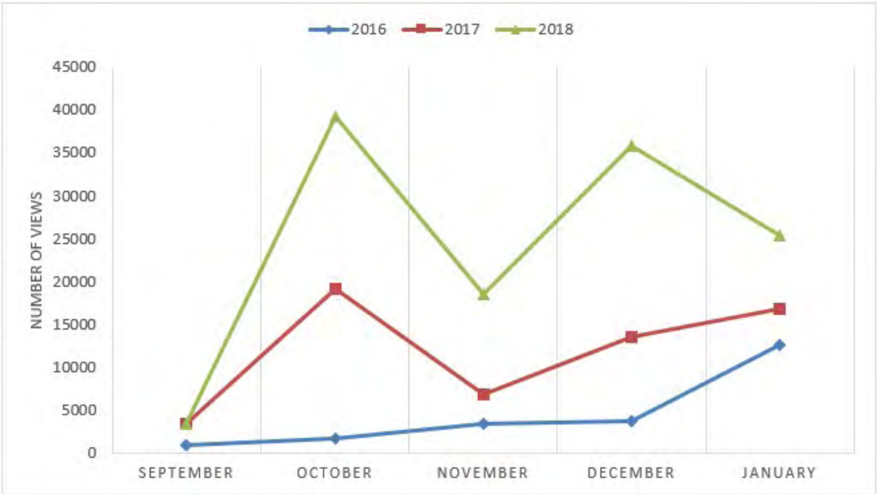

Figure 7: Student – activity and content views, 2016-2018 (source: own calculation)

Figure 8: Student posts, 2016-2018 (source: own calculation)

DISCUSSION

We understand that the issue we are dealing with is not new and has been addressed internationally for a longer time. In general, the vast majority of authors believe that if we want to educate students effectively through e-learning, it is necessary to take into account their personal qualities, which affect how students learn. The material can be then adapted to individual students or groups of students.

In the study of this issue, it was found that many authors remain only in the theoretical model of personalisation of e-courses and their conclusions are based only on the simulation of the behaviour of virtual students in VLE. The results of the experiment presented in this article are based on real data collected during the academic years 2017/2018 and 2018/2019 on a sample of students characterized in previous chapters. One of the most commonly used LMS for the realization of personalised learning is Moodle, which after the careful analysis was chosen in this case for experimental purposes too (Mudrák, 2018). For this reason, there was an effort to select the publications dealing with this issue those that also work with a physical sample of students in the Moodle environment.

The experiment conducted by Mironova et al. (2015) included 300 students of economics, social and technical sciences participating in e-courses in computer science. Students were divided according to the results of the entrance test into 3 groups - beginners, intermediates, and experts. The results were compared between a control and an experimental group of 150 students. Students of the experimental group were tested for their preferences of learning styles by the ILS questionnaire and based on the results they were recommended study material. This approach was found to have a positive impact on the experimental group and their acquisition of new knowledge showed by better test results.

Karagiannis and Satratzemi (2018) created 2 programming courses with the same content for their experiment, but an adaptive approach and progress bar was used for the experimental sample of the students. The analysis presented by the authors aimed to find out via attitude questionnaire whether their developed methodology helped students to improve their learning results, to learn more easily, and whether the motivation of students to study was increased. In their first feedback, they found out that implementing adaptive techniques did not affect the usability of the system. Secondly in the latter case, they found a statistically

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significant difference between the experimental and control group in terms of study motivation. According to the results, the experimental group was more motivated to study and also assessed the use of adaptive techniques as helpful in gaining new knowledge.

Kuchárik and Balogh (2019) used *Book* and *Quiz* activities in their experiment. In the end, however, they did not achieve such an improvement in the final assessment of students as they expected. A solution that could contribute to more improvement in learning outcomes could be the use of the *Quizzes* with personalized feedback (Mudrák, Turčáni and Burianová, 2018).

The results obtained from the research activities of the authors of the article are relevant for the monitored area from the point of view of comparing the results of foreign authors.

From the measurements, it is evident that the hypothesis H(1b) has been rejected. CON group students had better average scores than EXP group students from the pre-test. The observed difference in initial knowledge was probably due to the fact that current students of computer science, who were involved in research activities, attended secondary schools with various specializations. That was confirmed, when a statistically significant difference in initial knowledge was found also in groups divided according to a secondary school. There the EXP_TS group achieved on average better results than the EXP_OS group. These findings conclude that the initial knowledge of LSC students is not at the same level and hypothesis H(1a) has been rejected. It also shows that students coming from technical secondary schools have better predispositions for studying the subject of LSC. Based on the analysis of the results obtained by the research methods of the mentioned students it can be concluded that this fact should be taken into account when choosing the composition of individual research groups. From these findings, it can be answered in Q1. New students have a different level of initial knowledge.

Based on the results presented in Table 3, H(2) has not been rejected. It was found that differences between EXP_TS and EXP_OS groups of students, who studied by using the personalized e-course were balanced in the post-test. Both groups have improved. It follows that the attended secondary school has no impact on the output knowledge if the students studied through the personalized e-course.

From the results of the post-test of the EXP_TS and EXP_OS groups, it was found that the secondary school attended does not affect the output knowledge of students studying through a personalized e-course (answer on the Q2).

The entry questionnaire revealed that new students have different levels of motivation. Based on the results of the evaluation questionnaire, students declared the positive impact of a personalized e-course on their motivation to study (answer on the Q3).

An interesting finding was that H(3), which was formulated as an alternative hypothesis, has not been rejected. A positive correlation was found between the wanted grade from LSC subject before and the real grade from the final exam. Therefore, we believe that this is a factor reflecting the motivation of students to study a given subject. This finding should be considered when evaluating results in the future.

The results also show that the created personalised e-course has a significant impact on the efficiency of students' knowledge acquisition as a classical (non-personalised) e-course. It is highly likely that the better results of the EXP group in the post-test, as opposed to the CON group, are the result of the personalised e-course application. Hypothesis H(4) has been rejected. From the calculated values, it is concluded that the EXP group students showed better post-test results compared to the CON group. By testing H(2) and H(4), the Q4 was answered. It was found that the use of personalized e-course has a positive effect on the level of students' output knowledge.

From the ILS questionnaire results, it was found that students have different learning styles. But we cannot answer Q5 with absolute certainty. We conducted this survey repeatedly over the years on several samples of students. It was found that students in all surveys have a stronger tendency to prefer the same learning styles: Active, Sensing, Visual, and Sequential.

The proposed methodology described in this article was also verified by comparing the activity based on student logs in Moodle for the last 3 years. Based on the obtained data, we could answer on the Q6 that the use of Moodle adaptive tools in a personalised e-course had a positive effect on student activity.

Data obtained from questionnaires, pre-tests, post-tests were processed and evaluated to improve education in the AI. These findings represent a good direction in the area of the quality of achieved results in computer science subjects for students studying via the described methodology.

CONCLUSION

The main goal of the article was to present the methodology we created and verify its impact on students' learning outcomes as well as the overall effectiveness of studies. Based on the research questions and the above results, we consider the main goal to be fully met.

During teaching activities in the educational process, we constantly encounter insufficient personalisation of education for students who come to university education with different quality and quantity of knowledge in the field of study they have chosen. Based on this knowledge it is necessary to devote more attention to the analysis of the student's condition, the level of his or her knowledge in the given subject as well as the procedures of the educational process. For this purpose, e-courses were created for selected subjects on DI at UKF, which were subjected to thorough analysis to identify and remove all the shortcomings affecting the quality of personalised content of provided e-courses. Using the methodology described in this article, there was an opportunity to compare the impact of two different approaches and procedures on the effectiveness and level of students' knowledge.

This article is an extended version of the conference paper by Mudrák, Turčáni and Burianová (2019). The main points of the extension are:

- more detailed analysis of the issue
- the extended methodology of the personalized e-course with a specific model
- more detailed research methodology with new results

The creation of the personalised e-course methodology and its application proved to be an important activity, which had the most significant impact on the students' output knowledge and activity during the term. We assume that this fact was reflected in the students' achievements in the post-test. However, it should be stressed that the output educational effect could be influenced by the personality of the teacher/tutor, as it was a form of blended learning.

Unpreparedness or not enough will of teachers to implement personalisation into e-education can be one of the threats. This appeared in the research by Caputi and Garrido (2015), where teachers preferred their own concept of e-course planning to the suggested methodology of personalised e-course.

In the future, we will try to evaluate and continuously update all findings regarding education through a personalised e-course. The decisive factor will be the use of Moodle's adaptive options and the use of an appropriate e-course structure using personalisation options. Applying the proposed concept is expected to increase not only the effectiveness of the educational process but also to improve the results in terms of knowledge gained by studying via the proposed e-course.

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