PERSONALIZATION OF STUDENT IN COURSE MANAGEMENT SYSTEMS ON THE BASIS USING METHOD OF DATA MINING

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ABSTRACT
Individualization of learning through ICT allows to students not only the possibility choose the time and place to study, but especially pace adoption of new knowledge on the basis of preferred learning styles. Analysis of learning processes should give the answer to difficult questions from pedagogical and psychological theory and practice. Count of scientific studies that should represent the results of systematic and long-term oriented studies in this area is still few. With the Learning styles and possibilities of their application in the context of e-learning addresses many experts. These experts predict that student should know, which Learning style is best for him, or predict that alone student knows when is the right time to try it differently. For determination of learning styles and personalization of student in Course Management System are used various techniques. In the paper we present the use non standard of techniques of data mining - data mining based on the use of interactive animations in e-learning courses. With this method of data mining we can get a complete overview of the activities of the student and on the basis of the definition of so-called social rules we know adjust to educational content.

INTRODUCTION
Mass education in a classroom or with the help of classic e-learning is not able to respond to individual needs of a studying individual. Some students are restrained and bored by it, for some, on the other hand, it is too quick and they do not manage understand everything or the education style of each teacher does not have to be suitable for them (Balogh et al., 2011). Other students are satisfied with the pace of education, but they may not be satisfied with the teaching style of a particular teacher. Therefore, such students come to dislike the teachers and subjects they teach, which results in them having worse results (Brusilovsky, 2003; Chang, Kao and Chu, 2009). The suggested reasons lead to the idea of the optimization of the learning process through the use of individualization of education. Individualization of education represents each student's way of learning with regard to their previous knowledge, skills and their learning style (Kolb, 1984; Jeong, Choi and Song, 2012). A set of attitudes and behaviors which determine an individual's preferred way of learning is considered as a learning style (Honey and Mumford, 1992).

Learning styles have been a subject of extensive research (Coffield et al., 2004; Cohen and Weaver, 2006; Robinson, 2002), however the research focuses predominantly on their identification and classification. A team of experts dealt with the research and processing of the theory of learning styles in the Czech Republic (Takacs, Sarmanova and Kostolanyova, 2011; Simonova and Poulova, 20133). In Slovakia there exist only a few experts dealing with this sphere of pedagogy (Burgerová, 2001;Turek, 2002). The work by (Mares, 1988) served as a basis for the research of the Czech and Slovak experts.

In general, the purpose of the theory of processing and evaluation of individual styles of teaching is the proposal and solution of the problem of individualization of educational process. If we put together the essence and principle of e-learning and the request for personalized learning, we gain a relative new research area – adaptive learning. Optimal adaptive process will respect students' differences based on their learning style and with regard to their changing knowledge and skills during the course of the study in the course. On the basis of identification of personal characteristics and qualities, the students will be provided with a study material that suits them the most (Kostolanyova, Sarmanova and Takacs, 2011). We assume that personally tailored education accenting student's requirements, preferences, and positive sides of learning (we do not support surface learning, remembering without understanding, etc.) will become an optimal and effective form of education. It will make new knowledge easier to remember and more permanent.

ADAPTIVE EDUCATIONAL THEORY (LEARNING STYLES IN E-LEARNING)
Quantum of pedagogical and didactical principles (rules) form the theoretical basis for the formulation of adaptive educational theory (AET). These rules are based first of all on the following approaches:
- Komensky – systematic and methodical approach,
- Gagne – result can be accomplished by elementary steps,
- Bloom´s taxonomy – 6 levels of knowledge (remembering, understanding, applying, analyzing,

synthetizing and the ability to evaluate information) for successful realization of partial obligations, which are intensified during the course of education as to their degree of difficulty,
- Theory of program teaching (Skinner) – division of the contents of education into smaller wholes, their verification and reaction to the comprehension of the contents of education,
- Adaptive hypermedia systems (Brusilovský) – feedback and evaluation of behavior of the student during the process of education – journaling the process of teaching.

By reason of inconsistently processed classification of learning styles it is possible to meet with various models of classification of learning styles in the area of AET (most frequently Shulman´s or Felder-Silverman´s model).
Shulman's model (TPCK) – Conjunction of the pedagogical and contentual dimension means understanding and solving the particular pedagogical situation with the use of suitable learning methods and forms with the aim to accomplish effectiveness of the educational process.
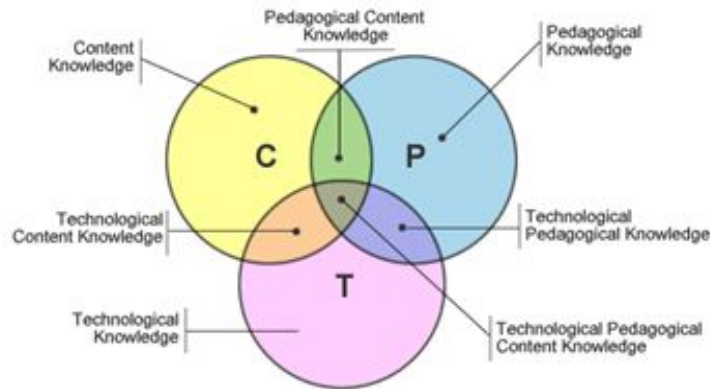

Figure 1: Shulman's model TPCK (Mishra and Koehler, 2006).

Based on the initial version (1986), Mishra and Koehler gradually extended it by a new dimension – technological aspect in 2006. Conjunction of all 3 dimensions is the defined work of the teacher with the current ICT with the aim to optimize and increase effectiveness of the educational process.

Felder-Silverman' model (FSLSM) - Felder and Silverman (1988) advocate that students learn in different ways: by hearing and seeing; by reflecting and acting; reasoning either logically or intuitively; by memorizing and visualizing and drawing analogies; and, either steadily or in small bits and large pieces. They also advocate that teaching styles vary, such as an educator's preference for lecturing or demonstrating, or for focusing on principles or applications.
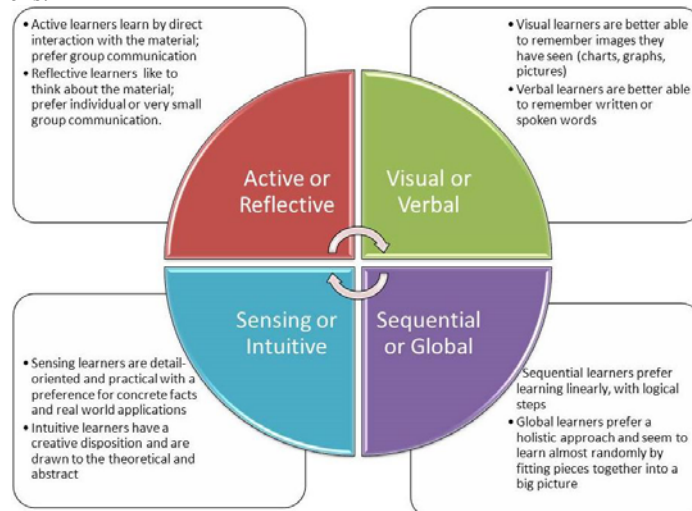

Figure 2: Felder-Silverman's model (Cater, 2011).

According to (Nakic, Graf and Granic, 2013) for assess students' learning style according to FSLSM, the Index of Learning Styles (ILS) is generally used (Felder and Soloman, 1997). It contains 44 two choice questions distributed along the four learning style dimensions, where one choice increments and the other decrements the score of the particular dimension. The resulting index of preference for each dimension is expressed by an odd

integer, ranging [-11, +11] since 11 questions are posed for each dimensions. The ILS questionnaire provides a very precise quantitative estimation of a learner's preference for each dimension of FSLSM.

MEDIA ELEMENTS AND METHODS OF DATA MINING

Learning management systems are commonly used in e-learning, but provide low level of adaptivity. By combining adaptation and personalization into LMS, a new kind of tailored learning environments which motivate learners can be built (Stefanovic, Stefanovic and Arsovic, 2013).

In case of utilizing e-learning systems, it is inevitable to utilize various techniques of data mining in order to expressly define fruitfulness of the continuous study (increment of knowledge, skills and experiences of the students) and based on the results to design a suitable learning style for the student.

Moodle accumulate amount of information which is very valuable for analyzing students' (Mostow et al., 2005). For example they can record student activities, academic results, user's interaction data, etc. Although some platforms offer different reporting tools, do not provide however specific tools which allow educators to thoroughly track and assess all the activities performed by their learners and to evaluate the structure and contents of the course and its effectiveness in the learning process. Very promising area for attaining this objective is the use of data mining.

Educational Data Mining (EDM) is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from the educational context (Romero, Ventura and Garcia, 2008). Methods of EDM is the automatic extraction of implicit and interesting patterns from large data collections. This methods is mainly used in the last decade for improve e-learning systems (Romero and Ventura, 2006). Data mining can be applied to explore, visualize and analyze e-learning data in order to identify useful patterns, to evaluate web activity to get more objective feedback for teachers' instruction and to find out more about how the students learn.

According to Romero and Ventura (2006) EDM is an iterative cycle which consists of the same four steps in the general data mining process as follows:
1. Collection data,
2. Preprocessing data,
3. Application of methods data mining,
4. Interpretation, evaluation and implementation the results to the pedagogical praxis.

Moodle logs activities including views and posts for all learning objects hosted in the system and provides „Reports" and statistics to help the content experts to improve the quality of eLearning courseware (Nagi and Suesawaluk, 2008). The records of the students' proceedings, created based on their activity in the course, however, do not contain information on the way of student's utilization of the material. The systems use log files to archive only data about the behavior of particular students in the course, which sources and activities s/he worked with, in what time periods, where from, etc. We can only find out whether the student has opened the material.

However, to get an idea of real transition of the students throughout the e-learning course, we need to consider several other important factors, one of them being the usage of implemented multimedia elements (e.g. interactive animations). All available electronic systems are able to record the time at which the student opened the website where the animation is situated and when he/she moved to another website. None of them, though, was concerned with the activity of the student from the point of view of manipulation with interactive media elements. Thus, the systems only stated the time that the students spent at the website where the media element was placed but the question if the student really worked with the element still remained unanswered. Therefore, it is only adequate to ask how to verify the activity/non-activity not only based on the transition throughout the course (opening the lesson, filling-in the quiz), but also via the detection of mouse movement or stating the interactivity of the student with the study material.

In the literature it is possible to meet with various attitudes to the definition of the concept multimedia. According to Neo and Neo (2004): „*medial elements can be differentiated as to the ability of perception (sentience) and control into text, graphic, animation, video and sound*". Rahman et al. (1996) extended this definition as follows: „*multimedia represent technology allowing for introducing text, sound, pictures, animations or video using interactive method*". In connection with learning styles Sonwalkar, however, uses 6 medial elements (the sixth being simulation), while these elements are interconnected by interactive aspects of

learning (Sonwalkar, 2001). Learning styles can be characterized according to Sonwalkar based on: L1 = apprenticeship; L2 = incidental; L3 = inductive; L4 = deductive; L5 = discovery.

If we reflect on interactivity as a medial element, it is interesting to read the statement of Shterev (2005): „*Any media element is presented by its start and also by its duration. It may be nominal, maximal and minimal. The starting time and duration define 2D temporal space*".
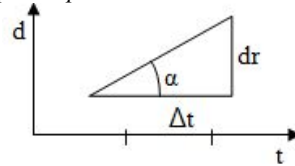

Figure 3: Temporal-spatial dimension of medial element from the point of view of 2D temporal space (Shterev, 2005).

Δt – time of duration of medial object
dr – real time of duration of the object
The correlation dr/Δt=tgα expresses the rate of speed of playback of the medial object, i.e. speed of reproduction.
Besides temporal-spatial dimension, interactivity can be evaluated also based on these three viewpoints:

1. Frequency (how frequently can the user react),
2. Possibilities of choice (how many choices can the user have at his disposal),
3. Significance (to what degree the decision of the user will influence the fact which will happen).

APPLYING DATA MINING TECHNIQUES ON THE BASIS USING INTERACTIVE ANIMATIONS IN LMS MOODLE

The reasons described above led us to develop a module which would, together with the original module "Reports", supply a complete report on student's activity even in cases when interactive media elements are implemented into the study material. We named it Interactive Element Stat (IES). The module was being developed since 2010 and was designed and programmed at the Department of Informatics at the Faculty of Natural Sciences, Constantine the Philosopher University in Nitra as the supporting system for the area of the analysis of educational activities of the students in LMS Moodle. Researching the current state of the issue, we found that no such kind of module has yet been developed, one that would be strictly aimed on evaluation of student's work with implemented interactive media element.

Main requirements on the module:
- the option of results display selection (whether the statistics is to be done for all the interactive media elements in the e-learning course or only for a particular interactive element),
- in statistics for the entire course, it is necessary to display a list of all the interactive course elements that were worked with, number of accesses to each of the elements, number of clicks, total time of student's work with the element,
- in statistics for a particular interactive element, it is necessary to display the name of the student who worked with the element, time spend on the work, student's way of manipulation with the element, what buttons were pressed, etc.,
- in statistics display, the option of time period selection is necessary,
- the statistics has to enable export into MS Excel format for further processing of the data,
- the teacher has to be able to delete the created statistics and start gathering new data from the beginning.

The standard module in development Course Report was enhanced by a mod.php file, which includes an assigned reference to the module itself, which is displayed in the Module report list. The file is designated to control whether the user has sufficient privileges to display the reference, if so, the reference will be displayed. After clicking the link, the module itself will open, specifically the index.php file. This file represents the main screen of the graphic module with two tabs. The Default tab contains a form for choosing the type of statistics and the time period. The Tools tab contains two buttons to delete the recorded statistics (Figure 4).
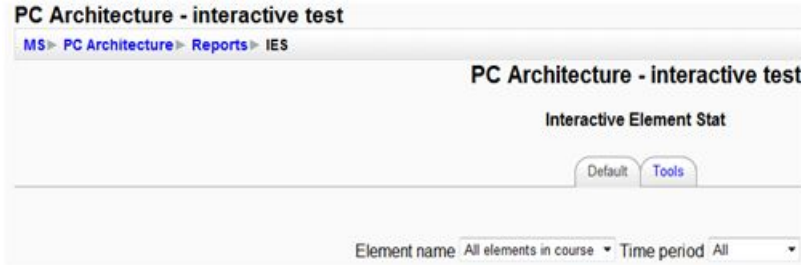
Figure 4: Module Interactive Element Stat

The module form displays the two standard Select boxes. The first one contains a list of all the course elements that were a part of any activity. The second one is used to choose the time period of statistics record. The form can be submitted using the Submit button. An important part of the index.php file is a safety control, in which we determine whether, the user:

- is working with an existing course,
- is currently logged in,
- has sufficient privileges to work with the module.

The statistics display itself uses a table format; it is possible to display the main statistics for all the course elements using graphs. Designing and developing the module, we decided for two graph display, in which the first graph shows the number of interactions with a particular media element and the second one shows the number of accesses to the element in the framework of the whole course (Figure 5).
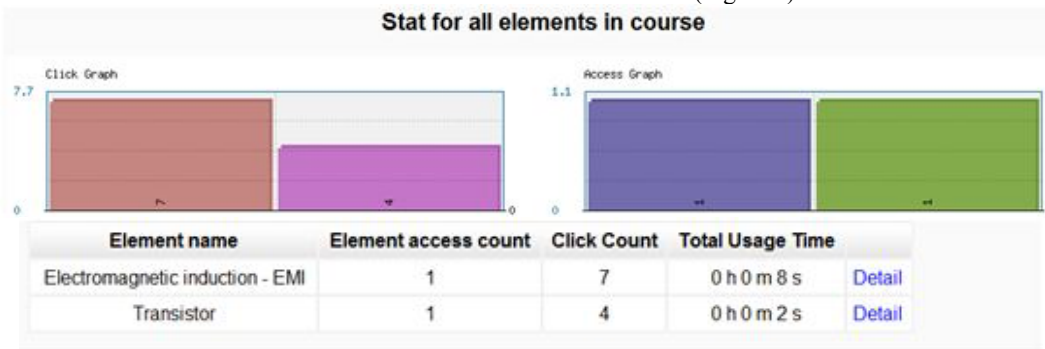

Figure 5: Stat Results statistics and graphical evaluation Axis x: interactive element name, axis y: total number of accesses or the number of performed actions during the accesses.

The structure of the file exported to MS Excel is unified for all types of statistics provided by the module; it contains the name of the statistics, statistic data from the table and informative foot with the name of the module and time of the export itself.

CASE STUDY OF APPLICATION OF THE METHODS OF DATA MINING IN THE SPHERE OF PERSONALIZATION OF STUDY MATERIAL FOR THE STUDENT
According to Romero, Ventura and García (2008) Moodle does not provide a basic statistics module in which the teacher can obtain specific reports about detailed statistics about every single student's performance (how many hours on the site, how much time at every activity, etc.).

This problem we partially removed using module IES. Using information obtained from module IES we can detect more easily students with some learning problems, for example, students with a very low number of accesses and offer them a suitable learning style.

Therefore, we introduce so called association rules. Association rule mining is one of the most well studied mining methods (Ceglar and Roddick, 2006). Agrawal et al. (1993) defined rules for techniques of data mining in this way: given a set of transactions, where each transaction is a set of items, an association rule is a rule of the form X → Y, where X and Y are non-intersecting sets of items. Each rule is accompanied by two meaningful measures, confidence and support. Confidence measures the percentage of transactions containing X that also contain Y. Similarly, support measures the percentage of transactions that contain X or Y.

These rules of data mining have been applied to different learning management systems for building a recommender agent that could recommend on-line learning activities or shortcuts (Kapusta, Munk and Turcani, 2009), for automatically guiding the learner's activities and intelligently generating and recommending learning materials (Lu, 2004), for determining which learning materials are the most suitable for students (Kostolanyova, Takacs and Sarmanova, 2013).

Rules are often applied to the whole system, which becomes adaptive at the personalization of the student, or to the particular part of the e-learning system, most frequently to the teaching part offering study material based on a suitably designed learning strategy (of the suitable learning style). In this case, the model FSLSM applied to the conditions of creating and providing the study material in the system Moodle is most frequently used.

The Learning Management System (LMS) Moodle enables teachers to create a lesson in form of a series of HTML pages. Lessons are created through the Lesson module or module Book. These modules are modules of third pages.

The module Book allows for simply creating multi-page texts, similarly as we are used to do it from printed books. We are not pressed to create many sources in HTML format of page; we can put all into one, thus at the same time increasing lucidity of the course. Possibility to create hierarchical structure of chapters and sub-chapters is also an asset (Svec, 2007).
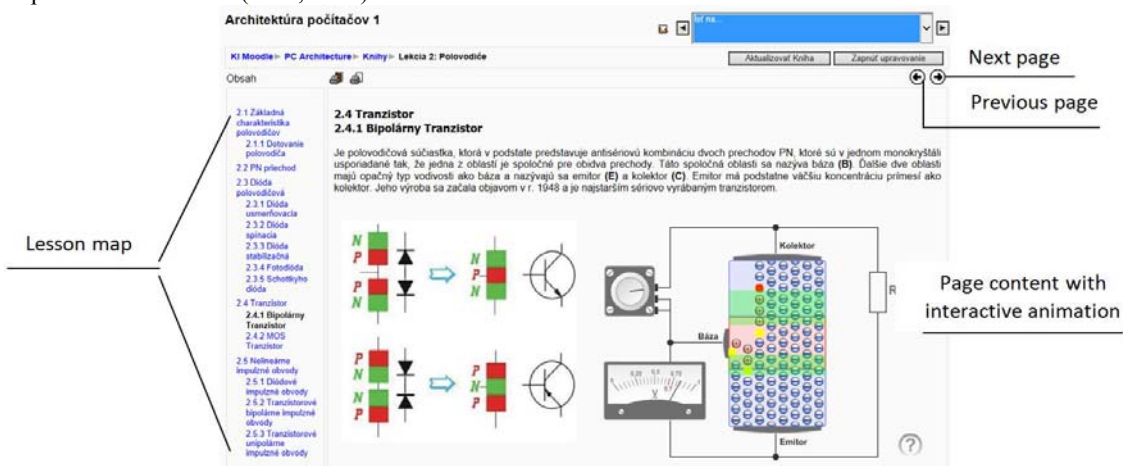

Figure 6: Stat Interface and typical content page created by the module Book with implemented interactive animation (Transistor), from original course in Slovak language.

The teacher decides how many buttons will be on each content page and for each button what is the target page ("jump to"). The "Next page" button allows direct guidance of a student, i.e. he/she will follow the default path determined by the teacher. The other buttons along with map of the lesson allow the students to create their own path through the lesson (Nakic, Graf and Granic, 2013). The module Book is therefore not adaptive. For providing advanced adaptive behavior, we modified the original module and this module has name AdaptiveBook. This module enables the creation of lessons adapted to the learning styles of students according to FSLSM.

The module AdaptiveBook was used in e-learning course named Architecture of computers I, which is focusing on logic systems (winter semester of academic year 2013/2014, students of 1st year of the field Applied informatics). Students studying in the course were graduates of various secondary schools: secondary school of electrical engineering (15), grammar school (2), business academy (1), hotel academy (2).

In order to be able to match the suitable learning style to each student, ILS questionnaire was implemented into the module AdaptiveBook. At implementing the questionnaire we draw from experiences of (Nakic, Graf and Granic, 2013), who implemented a module of similar character into LMS Moodle.
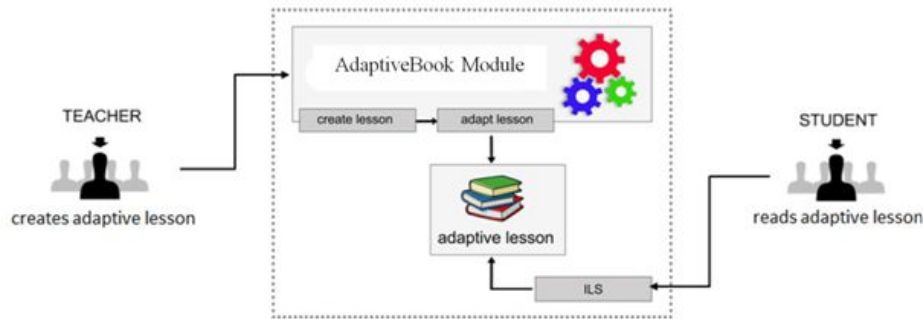
Figure 7: Teacher's and student's interaction with AdaptiveBook module (Nakić, Graf and Granić, 2013)

By filling the ILS questionnaire out at the beginning of semester and applying association rules the student obtains personalization in the form of adaptive provision of the study material. By applying the module AdaptiveBook and the following continuous evaluation of study results during the semester we found out that in spite of the questionnaire filled-out and applying the association rules some students reached unsatisfactory study results. All these were the ones who did not graduate from secondary school of electrical engineering.

By monitoring the students´ activities using the standard configuration Report in Moodle it was not possible to determine their complete activity. Defining activity is an important step in personalization. Based on the information on the movement of the student in the course it is possible to apply association rules more consistently. On a regular basis, the module AdaptiveBook works on the basis of an allocated learning style to the particular student. But what if this style changes during the study due to unpredictable circumstances?

Based on access to the study materials we found out that students despite the provided learning style had problems with correct analyzing and understanding the provided study material. That is why they utilized very frequently a back transition to the previous parts of lessons, which was rather chaotic despite the module AdaptiveBook (Table 1).

Table 1: Interactive matrix of transitions between individual lessons

	Start study	L1	L2	L3	L4	L5	L6	L7	L8	L9	End study
Start study	0	2450	852	356	124	258	689	346	734	428	45
L1	892	0	1987	556	87	2190	324	222	318	110	23
L2	634	1554	0	2041	918	796	369	567	216	257	51
L3	176	652	347	0	1321	821	221	705	599	375	74
L4	841	869	490	1458	0	1878	478	756	311	338	36
L5	654	512	1591	428	998	0	2887	568	850	151	111
L6	317	974	627	898	1370	350	0	1655	152	185	34
L7	268	498	623	495	580	915	1331	0	1201	100	174
L8	954	825	829	461	613	558	471	434	0	1637	190
L9	438	604	268	947	864	466	420	623	350	0	255
End study	526	249	315	185	277	216	265	170	57	46	0

The value in the column (above 1000) expresses the fact that the students realized the given activity most frequently and after it they continued with another activity with the highest maximal value situated in the nearest column. In case that there is more than one maximal value in the column of interaction matrix, it means that the student returned to this activity during the course of his study.

On this account we interconnected the IES module with the one of AdaptiveBook in order to identify the students´ activity more easily. By interconnecting the modules we obtained a tool, which allowed us to mine the data directly at activities of the students with the study material and propose continuous changes in the learning styles to them. These changes resulted in providing study materials, or offering a choice of its parts through implemented interactive animations. E-learning course has been considerably simplified. The amount of text and pictures decreased. They were replaced just by this type of interactive media element.

Connection of IES modules and AdaptiveBook allowed the students for fully utilizing interactive possibilities of implemented animations and finding one´s way in the study material by means of hyperlinks, which continually appeared in them. Provision of hyperlinks was realized based on the results of data mining from IES module and applying association rules. The prerequisite for the provision of hyperlinks was for example repeated

utilization of one and the same function – a view of some of the animation parts, or a particular active work with animation, or its part.
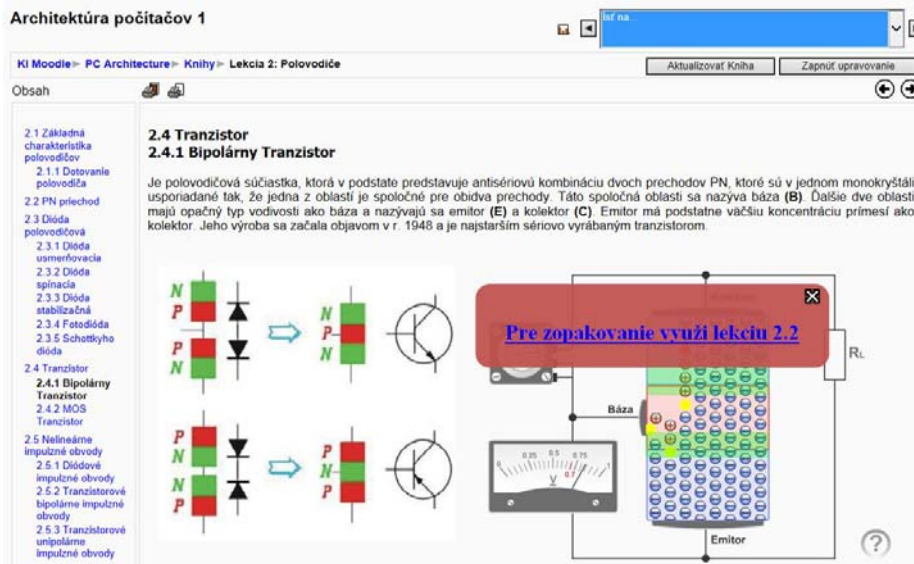

Figure 8: Adaptive provision of hyperlinks by the module AdaptiveBook and module IES, from original course in Slovak language

After a repeated analysis of accesses at the end of the semester and setting up of interaction matrix of the transition of the students through e-learning course we found out that students passed the course fluently. It appears from this that a suitable learning style for each individual was chosen and the study material was adjusted to the possibilities and abilities of every student.

Table 2: Interaction matrix of transitions between individual lessons (after the modification by IES module and AdaptiveBook)

	Start study	L1	L2	L3	L4	L5	L6	L7	L8	L9	End study
Start study	0	1609	720	662	792	558	822	521	880	830	43
L1	955	0	1595	435	849	874	729	912	420	218	62
L2	949	674	0	1455	896	411	862	325	930	538	30
L3	958	449	174	0	1355	297	808	375	358	994	42
L4	221	706	667	721	0	1279	831	480	814	266	53
L5	551	656	742	505	378	0	1004	458	609	292	20
L6	156	795	302	804	928	429	0	1108	351	203	175
L7	663	694	251	846	956	892	676	0	1184	161	42
L8	982	356	826	703	629	710	615	123	0	1523	262
L9	519	546	334	590	495	554	863	294	1187	0	358
End study	259	177	142	236	112	190	127	90	134	217	0

CONCLUSION

According to Felder and Silverman (1988), active learners are comfortable with problem-solving activities and group discussions, they prefer answering questions and doing exercises but less theory and examples. In contrary, reflective learners learn by reflecting on the matter and thinking things through.

To determine the learning strategy (learning style) is not a simple process. In the contribution we gave an example that despite filling out the structured questionnaire ILS the allotted learning style to the student need not necessarily suit him during the whole semester. At present, authors of professional publications dealing with the implementation of ICT in education (Bhuasiri et al., 2012) point to the fact that the development of ICT is higher than their actual use, and requires thinking about the elements that we need to improve to produce ICT effective integration in educational processes (Melia, Gonzales-Such and Garcia-Bellido, 2012). As Internet use has proliferated, e-learning systems have become increasingly popular. Many researchers have taken a great deal of effort to promote high quality e-learning environments, such as adaptive learning environments, personalized/adaptive guidance mechanisms, and so on. These researches need to collect large amounts of behavioral patterns for the verification and/or experimentation. However, collecting sufficient and correctly

behavioral patterns usually takes a great deal of time and effort (Chang, Huang and. Chu, 2009).

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