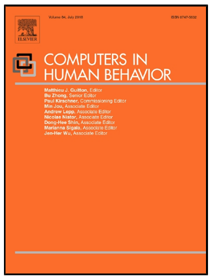
Accepted Manuscript



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PII:	S0747-5632(18)30259-0
DOI:	10.1016/j.chb.2018.05.033
Reference:	CHB 5542
To appear in:	*Computers in Human Behavior*
Received Date:	03 February 2017
Accepted Date:	25 May 2018

Please cite this article as: S. Hubalovsky, M. Hubalovska, M. Musilek, Assessment of the Influence of Adaptive E-learning on Learning Effectiveness of Primary School Pupils, *Computers in Human Behavior* (2018), doi: 10.1016/j.chb.2018.05.033

Assessment of the Influence of Adaptive E-learning on Learning Effectiveness of Primary School Pupils

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Assessment of the Influence of Adaptive E-learning on Learning Effectiveness of Primary School Pupils

ABSTRACT

The paper deals with assessment of the influence of adaptive e-learning as a part of learning analytics on learning effectiveness of primary school pupils. E-learning exercises containing implemented adaptive elements were created in accordance with the Bloom's Taxonomy. Within the pilot study the authors detected high percentage success rate during e-learning exercise completion. This leads to formulation of the question „Can any e-learning exercise of lower cognitive levels of Bloom's taxonomy be skipped without affecting the cognitive thinking for solution of the e-learning exercises on upper cognitive levels of Bloom's taxonomy?" To answer the question, the algorithm of adaptive e-learning was defined and hypotheses were established. The research was carried out as pedagogical experiment comparing the results of both experimental and control groups of pupils. The research hypotheses were confirmed by statistical analysis of the research data. The results confirm that adaptive features of e-learning can be implemented in the primary education. The research results confirm the fact that educational objectives can be achieved with some pupils more effectively. Consequently, the implementation of adaptive elements into e-learning at the primary school supports an individual approach when completing e-learning exercises according to the principle of cognitive computing.

Keywords: Learning analytics, Cognitive computing, Adaptive e-learning, Primary education, Learning effectiveness, Bloom's taxonomy.

1. INTRODUCTION

Since 2013, the authors have been dealing with the issue of implementing e-learning exercises in primary school pupils' instruction. The research presented in this paper had been conducted at the Primary school Bratří Čapků in Úpice. Within the pilot project at this school, e-learning materials were created for primary school pupils to support the instruction of the following subjects: Mathematics, Czech language, English language and Science. (see Section 2.1).

In the previous research, the authors (discussed the following questions: how e-learning exercises are accepted by pupils, how e-learning exercises motivate pupils to practice the particular subjects, whether the primary school pupils are able to work with ICT technology and e-learning exercises, and whether the use of e- learning materials improves pupil´s performance.

E-learning materials were created by teachers of the Primary school Bratří Čapků in Úpice in cooperation with the researchers. The materials were developed reflecting both e-learning specifics (see Section 1.1) and e-learning materials for primary education (see Section 1.2).

The e-learning material consists of sets of e-learning exercises. The set of the exercises is divided into five sub-sets. Each sub-set consists of three exercises i.e. the set of exercises includes 15 sub-exercises in total. The difficulty of the e-learning exercises is gradually increasing. The exercises of each sub-set develop one domain of cognitive aims in Bloom's taxonomy (see Sections 2.1 and 2.2).

In the course of the previous research, the authors noticed that some talented students managed to perform sub-exercises of the lower domains of the Bloom´s Taxonomy correctly and in a short time. The authors found out that pupils are able to have the same learning progress in a shorter time, i.e. there was the possibility to increase their learning effectiveness.

This fact led the authors of the paper to the idea of introducing adaptive feature **based on principles of learning analytics and cognitive computing** into the school's existing e-learning system (see Section 2.3). Adaptive e-learning is based on the introduction of the Adaptive Learning Game Design (Lavieri, 2014) and the gamification model to education (Simoes, Redondo, & Vilas, 2013). The principle of adaptability is that, based on the given rules, the sub-exercise of the lower domains of Bloom's taxonomy is omitted in the course of e-learning exercise (described in detail in Section 2.3.3).

The authors realize that learning efficiency can be influenced by the introduction of adaptability to e-learning, therefore, they established the following research questions: 1. "Can effectiveness of primary e-learning training be increased by utilizing of elements of adaptive e-learning?" and 2. "Can any e-learning exercise of lower cognitive levels of Bloom's taxonomy be skipped without affecting the cognitive thinking for solution of the e-learning exercises on upper cognitive levels of Bloom's taxonomy?" (see Section 3.2). In order to answer the research questions, research hypotheses were established and the described research was conducted – see the Section 3.2.

The research results are presented and discussed in Section 4. In the research, the authors evaluate learning effectiveness using statistical methods. The learning effectiveness is introduced in Section 2.5. The research

results stated in the paper confirm that the implementation of adaptive features to e-learning of primary education leads to the increase in the learning effectiveness of the pupils.
The paper deals with in the literature rarely discussed issue of the use of e-learning in primary education (children 6-10 years) and thus it brings new knowledge in the field of learning analytics and cognitive computing for learning innovation. The paper also introduces new findings in cognitive computing in learning systems as it describes the implementation of adaptive elements into primary school e-learning. The issues of primary school e-learning and the introduction of adaptive elements as well as learning analytics into it are addressed, for example, in the works of Spylka and Sofianopoulou (2016) or Alstrup and Rootzen (2016).

1.1 The Specifics of E-learning at Primary Education

The goal of primary education is a transition of pupils from early family and childhood education into compulsory, regular and systematic education. It is based on learning, respecting and developing individual needs, capabilities and interests of each pupil (MSMT, 2014). The methods used in primary education should motivate pupils, lead them to the learning activity and to the realization that it is possible to search, discover, create and find suitable ways of solving problems. The primary education requires stimulating and creative environment that motivates the brightest pupils, encourages the less talented pupils, protects and supports the weakest ones (MSMT, 2013).
Nowadays, the information and communication technology (ICT) is used in everyday life. It develops the digital or computational literacy, which has to be reflected in the educational competencies (Futurelab, 2010). The children, who start school attendance, have already experience with ICT. Their experience has to be developed in the proper way (Holloway, Green, & Livingstone, 2013). The computational literacy should be cultivated.
The implementation of e-learning to education is one of the possibilities for the development of computational literacy at all levels of education. The e-learning has been widely implemented to education not only at universities, but also at secondary schools. There are primary schools implementing e-learning as a new and contemporary method of learning as well (NCCA, 2015). The primary e-learning has certain specifics related to primary educational requirements. The requirements on pupils at primary schools are significantly different in comparison with requirements put on students at higher level of education (NCCA, 2015). An analogous situation in the Czech Republic was described by Zounek and Sedova (2009).
During full time education, pupil's learning is driven by a leader (a teacher or parents). The motivation plays significant role. Only the motivation can "force" pupils to learn, although classmates are a supporting factor, too. In this context, it might be interesting to mention (Carmichael, & MacDonald, 2016) who emphasizes the fact, that direct help of a parent with homework has rather negative influence. Nevertheless, the other types of involvement, such as provision of a good home environment and pupil's motivation by parents, have positive effect on achievement.
The significant necessity of study via e-learning is the ability to self-study, responsibility, ability to organize and plan the time, computer literacy at a certain level and availability of technology. The ability to self-study is not fully developed by primary school pupils. The e-learning in primary schools can only support full time learning. The pupils taught via e-learning have to be supported by their teacher / leader / parent in primary education (Ofcom, 2012). Pupils should not be left in e-learning problems alone. The e-learning education has only a supportive character. It is an optional alternative. Primary schools use e-learning as a supplement or an extension of the traditional "full-time" education. It is suggested to implement the e-learning into primary education in the form of e-learning exercises for strengthening the curriculum (Goh, Bay, & Chen, 2015).
On the other hand, the advantage of e-learning is that the learners have during study a considerable degree of anonymity and discriminating factors such as appearance, clothing, race, gender are mostly irrelevant. The implementation of e-learning helps introverted pupils.
Regarding the fact**,** that the e-learning has only supportive character in primary education, the negative phenomenon like the lack of physical contact with their classmates or their teachers doesn´t occur.
As previously stated, a teacher plays important role in primary e-learning. Simultaneously his/her role changes. A role of a teacher at primary e-learning shifts to being a helper and a leader. This concerns also the primary school teachers. The conviction of authors about e-learning suitability for primary school teachers is supported by a study (Hrtonova, Kohout, Rohlikova, & Zounek, 2014). The study states that „*the factors which had no statistically significant impact (p > .05) included the teacher's age, gender, type of school, prior experience with e-learning*…". The very same opinion is supported also by a study of Pynoo, Devolder, Tondeur, van Braak, Duyck, W. and Duyck, P. (2011), which deals with the acceptance of digital learning environment in general.

1.2 The Specifics of Primary E-learning Material

The primary e-learning has to focus on motivational and differentiated approach with regard to the age and knowledge of a pupil.

The motivational character of the material has the most important role. To support the motivation of pupils the e-learning material should comply as follows (Hubalovska, 2015):

- the e-learning materials should support the full time education – an e-learning material should be designed as e-learning training exercises strengthening the curriculum;
- the e-learning exercises should be colorful, interactive, it should include pictures, etc.;
- the e-learning exercises should not be tedious, it should be partly action;
- the e-learning exercises should contain the elements of gamification;
- the difficulty of the e-learning exercises should be ascending, from the simplest to the most difficult exercises, in accordance with the Revised Bloom's Taxonomy.

Aguilera, Fernandez and Fitz-Gerald (2002) in their study emphasize the importance of addressing all cognitive levels of Bloom's taxonomy in e-learning materials. Their study suggests rules for creation of e-learning exercises that develop not only low levels of taxonomy (remember, understand), but also higher levels (apply, analyze, evaluate). The study dealt with the university level e-learning.

There are many development environments for creation of e-learning materials. The authors of the paper found the Hot Potatoes author system as the suitable tool for creation of a primary e-learning material. The author system Hot Potatoes was created by a team of researchers at the University of Victoria under the leadership of Bogdanov (2013). The exercises created in Hot Potatoes author system are very suitable especially for primary learning. It allows a large number of options for creation of interactive, interesting and attractive materials and exercises. Hot Potatoes enables insertion of pictures and sounds. Hot Potatoes has 5 modules, each of which is used to create a particular type of exercise that can be put in HTML format on the web site as interactive exercises (Hubalovska, & Hubalovsky, 2015). The exercises created in Hot Potatoes can be used not only on computers, but also on mobile technologies like tablets or smartphones etc. The significant advantages of this author system are that the principle of design and creation of the interactive exercises is easy and intuitive and the exercises can be created by anybody who can work with computer on the level of a common user.

The management (i.e. way of the pass through the exercises, recording of a success rate, access time and date, the time needed for exercise completion, etc.) can be realized by implementation of Hot Potatoes exercises to any learning management system (LMS). The authors find LMS Moodle most appropriate for the implementation. Linking two such systems represents shift in value from which both systems benefit. LMS Moodle communicates very well with Hot Potatoes (Hubalovska, & Hubalovsky, 2016).

2. CONTEXT

2.1 Project "Computer-Aided Preparation of Pupils"

The research presented in the paper was conducted in a Primary School in Úpice, Czech Republic. The internal school project "Computer-aided preparation of pupils" was conducted from 2013 to 2014. Within the project, the total number of 6600 e-learning materials for pupils from the 1st to the 5th grade of primary school in subjects Czech language, Mathematics, English language and Science were created. The e-learning exercises were designed and created by teachers of the school within the project.

The primary e-learning exercises were strictly created so that they develop the first five domains of cognitive aims in Bloom's taxonomy (Aguilera et al., 2002). This requirement was based on the project assignment and the project purpose had to be respected. The tasks were created in accordance with the Bloom´s Taxonomy of Educational Objectives, because it exactly corresponds to the requirements of the primary school curriculum organization. Each set is split to five Sub-sets. Each Sub-set consist of three Hot Potatoes exercises. These three exercises within the given Sub-set develop and evaluate cognitive thinking of one domain of Revised Bloom's taxonomy of educational aims. The order of the exercises is ascending in accordance with the cognitive aims of Revised Bloom's Taxonomy. Completing of exercises start with the exercises of the first Sub-set corresponding to the first domain of Revised Bloom's Taxonomy – Remember; the exercises of the second Sub-set correspond to the second domain of Bloom's taxonomy – Understand, etc. Final Sub-set consists of exercises developing the cognitive domain - Evaluate.

The exercises for the highest domain of the Revised Bloom's taxonomy (Create) are not used. Despite the fact that the construction of new exercises is useful and motivating activity, it is not suitable for e-learning, because presence of a teacher for evaluation of such tasks is necessary.

The exercise distribution within a single set of exercises is shown in Figure 1.

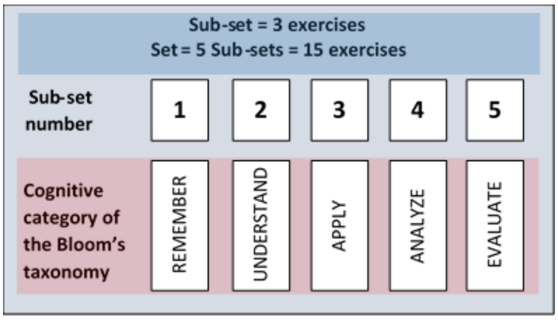

Figure 1. The exercise distribution within a single set

The exercises consist of different number of following screens – “sub-exercises”. Each screen can be created in a different Hot Potatoes module. The examples of the screens of exercises for individual Sub-sets are shown in the following chapter.

2.2 An Example of E-learning Exercises from the Perspective of the Revised Bloom’s Taxonomy

The exercises of the Sub-set 1 (*Remember*) practice and fix the lowest cognitive knowledge. The pupils practice and fix the knowledge acquired in traditional "full-time" education. The example of the exercise of the Sub-set 1 is shown in the Figure 2. The pupils consolidate their knowledge of multiples. They write multiples of numbers, they rank multiples of numbers from the smallest to the largest numbers and opposite. In this exercise, pupils consolidate memorizing a series of multiples of number three. In pedagogical practice, it seems that memorizing a multiplicity of multiples of numbers is useful for future quick and accurate calculating of multiplication and division by heart. The exercise is in accordance with the lowest domain of the revised Bloom´s Taxonomy – *Remember*.

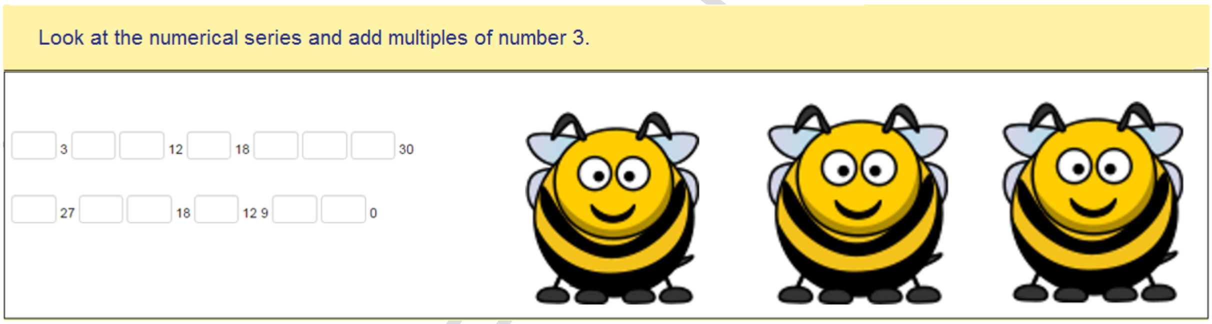

Figure 2. The exercise example of Sub-set 1 - Remember

The exercises of the Sub-set 2 (*Understand*) verify that pupils understand the curriculum. The example shown in the Figure 3 represents the example of an exercise for multiplication and division. The pupils complement the results, select and assign the correct results from the menu. In order to fulfill the task correctly, the pupil must understand both the mathematical record and the principle of the multiplication operation. In contrast to the previous exercise, the pupil cannot make do with the mechanical memory, the assignments are not organized according to the size, and the correct answer is to be found in menu containing several variants. The exercise is in accordance with the revised Bloom´s Taxonomy – *Understand*.

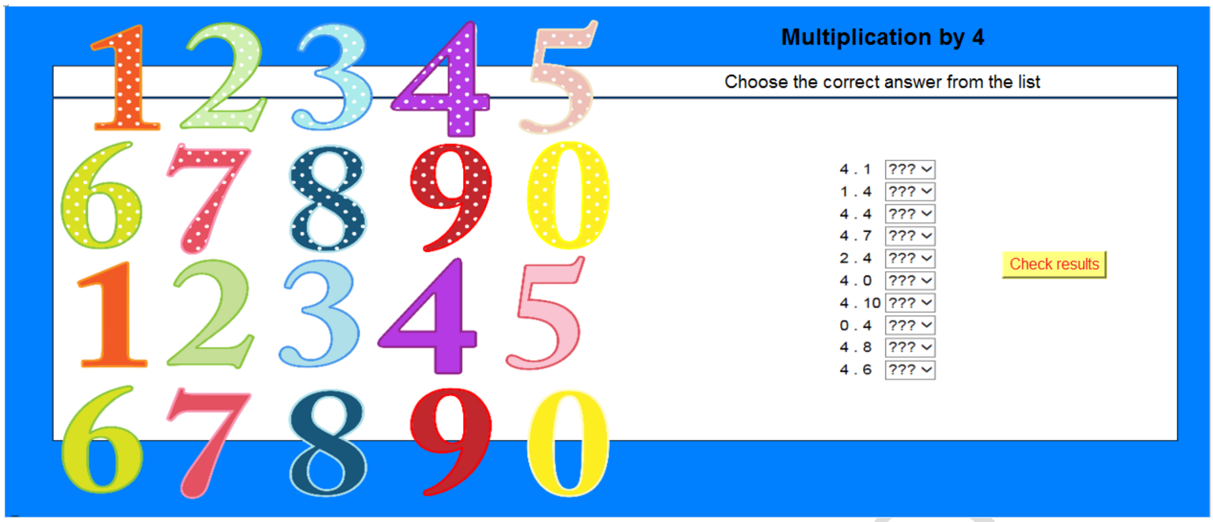

Figure 3. The exercise example of Sub-set 2 - Understand

The exercises of the Sub-set 3 (*Apply)* are intended for applying the curriculum. The Figure 4 represents an example of an exercise in which pupils apply their knowledge of multiplication tables. The example demonstrates applying knowledge of multiplication acquired in previous exercises. The pupil has to solve problems in new situations – he/she has to fill the number to different position of the expression. The pupil proves the ability to solve the problem. Although the tasks formally look similar to the previous ones and seem to be multiplication tasks, by omitting one of the factors, the task actually changes into a division task, in the second part the task is even more complicated by other numerical operations. Learned rules and numerical connections cannot be applied mechanically, but by putting them in a new situation, they become simple problem tasks.

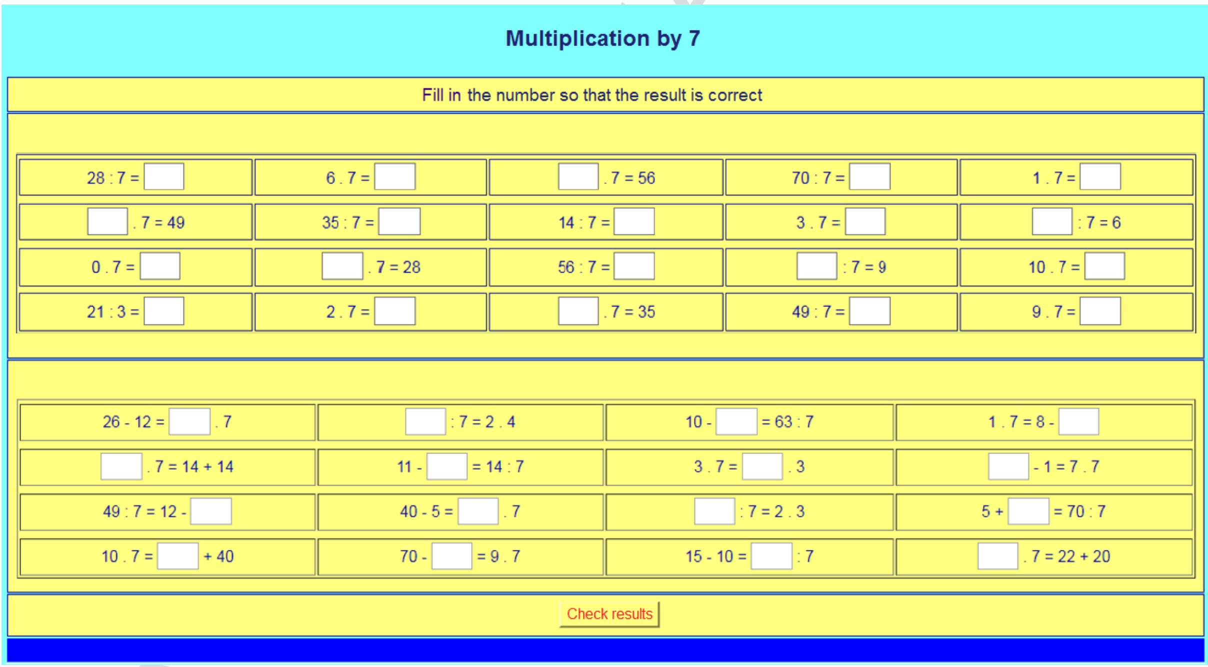

Figure 4. The exercise example of Sub-set 3 - Apply

The exercises of the Sub-set 4 (*Analyze*) develop in pupils the ability to analyze. The pupils have to understand the exercise, analyze the problem and find the correct procedure for calculation – see Figure 5. The pupils solve a simple numerical verbal task in the exercise. They must analyze the information read in the assignment, i.e. to analyze the given information, identify relevant information, identify related information, and subsequently find the right solution.

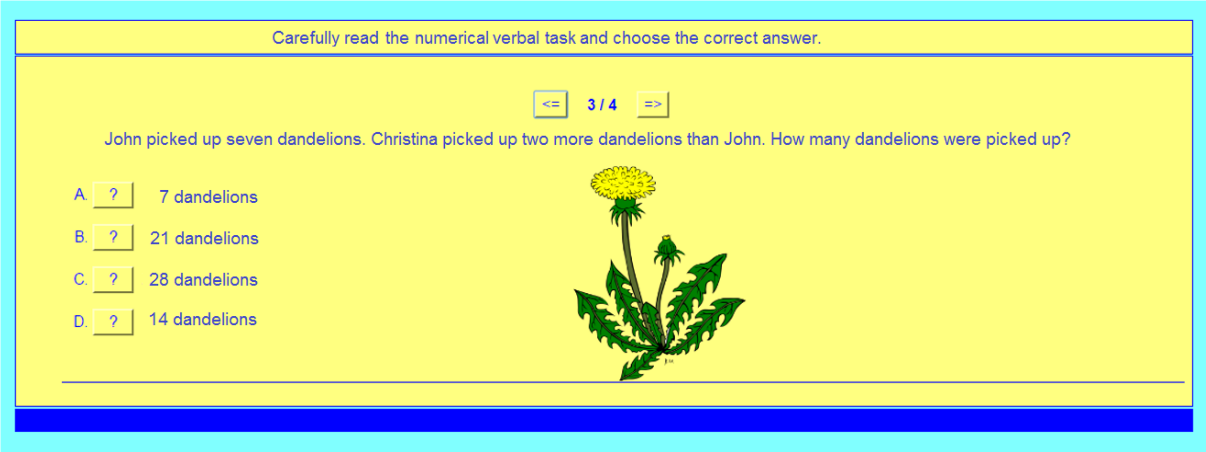

Figure 5. The exercise example of Sub-set 4 - Analyze

The exercises of Sub-set 5 (*Evaluate*) are the most complicated for pupils. Pupils solve numerical verbal tasks. They have to read with understanding to perceive the problem. The task consists of three possible and similar solutions. Based on the analysis of the information in the assignment, the pupil has to evaluate, which of the solutions is correct – see Figure 6.

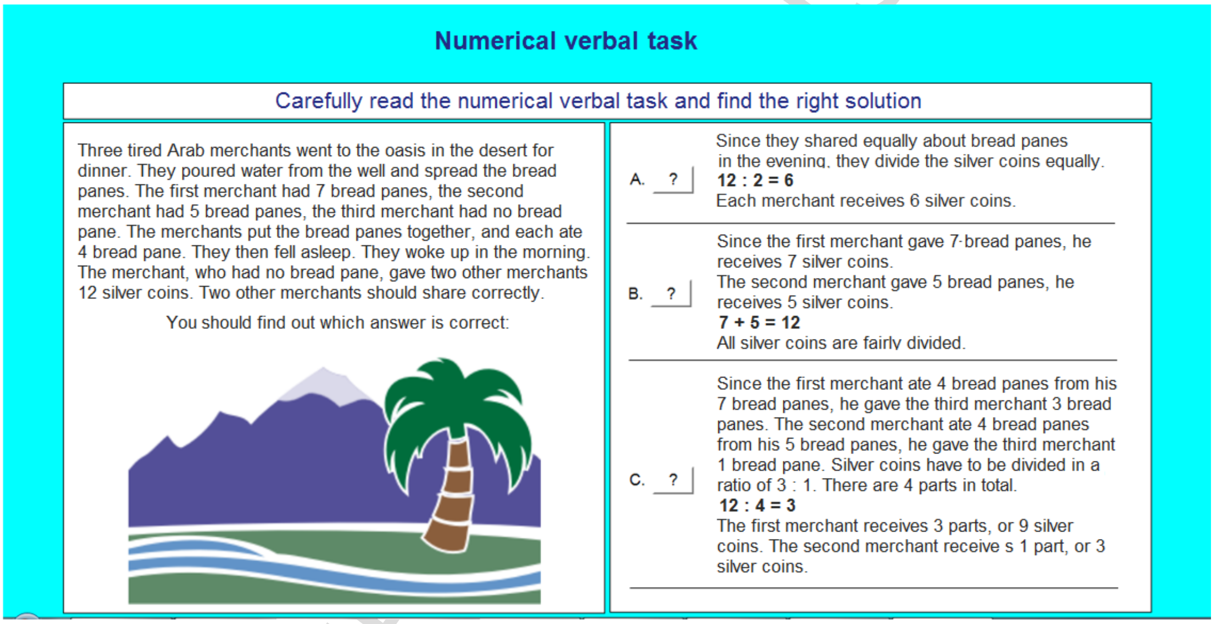

Figure 6. The exercise example of Sub-set 5 – Evaluate

2.3 The Adaptive E-learning

Within the pilot study, the authors focused on the evaluation of the results of pupils of the third grade in subject Mathematics in academic year 2014/15. The results of a randomly selected set of e-learning exercises were statistically analyzed. The selected set consists of exercises for training the multiplication table up to hundred (examples of the exercises are shown above). The main result of the pilot study (see Section 3.1) shows there is a high percentage of pupils with the success rate higher than 90 % (see Table 2). It seems from the results that completion of the e-learning exercises of lower educational objectives of Bloom's taxonomy would not develop cognitive thinking for solution of the e-learning exercises of upper educational objectives of Bloom's taxonomy. For some students the time spent by solving of "lower Bloom's exercises" might be considered useless.

The authors address the issue of how to increase efficiency of the completion of the e-learning exercises.

Regarding the fact the "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs." (Siemens, & Long, 2011), the authors deal with possibilities of implementation of **adaptive features** based on concept of **learning analytics** to already existing e-learning systems in Primary School in Úpice.

The term adaptive e-learning is understood as the method of learning which uses the computer for setting and controlling the optimal way of passing the e-learning material. The results of the research of Pavlik and Anderson (2008) confirm that adaptive e-learning significantly increases the learning outcomes. Fernandez (2003) in his study summarized adapt e-learning system in accordance with cognitive path from the lowest to the highest-level exercises. Recently, the term Adaptive Learning Game Design (ALGAE) was introduced by Lavieri (2014). ALGAE represents comprehensive adaptive learning model based on game design theories and practices and adaptive e-learning. Implementation of the gamification is addressed also by Giessen (2015) and Sanchez et al. (2016). Studies emphasize, that the e-learning gamification can be understood as a form of adaptive e-learning. The game principle in learning requires interactivity, multimedia support, to allow multiple performance, feasibility, increase in the difficulty level and transition to higher levels (Kiryakova, Angelova, & Yordanova, 2014). The strategy of gamification implementation into education is described in detail in e.g. (Simoes at al., 2013). Similarly, the importance of the implementation of gamification elements in the adaptive e-learning is stressed by Skuta and Kostolanyova (2016) and Paiva, Leal and Queiros (2016). They deal with principles of progress into higher, more difficult levels. Kinshuk (2014) emphasizes use of adaptive e-learning since the childhood stage.

The goal of adaptive e-learning is to make decision and defining the optimal way of learning process in order to increase learning outcomes. The increase of learning outcomes is in line with the concept of **cognitive computing**, because the goal of cognitive computing is to simulate human brain activity, help improve human decision making and increase learning effectiveness (Kelly, 2015)

As e-learning in general, adaptive e-learning in primary education is an insufficiently researched field. The elements of gamification mentioned above and ALGAE seem to be appropriate for their introduction at primary schools. Some better situations are at higher level schools. (Tosheva, Stojkovikj, Stojanova, Zlatanovska, & Bande Martinovski, 2017; Sweta, & Lal, 2017; Truong, 2016).

2.3.1 The E-learning Adaptation at Primary School in Úpice

The principles of ALGAE and gamification model were used in adaptation of the primary e-learning system in Primary School in Úpice. The adaptation of the e-learning focused on determination of optimal path for passing through e-learning exercises. The determination of the optimal path has to fulfill the requirement as follows:

- Learning and training effectiveness has to increase.
- Ensure that pupils feel busy and satisfied while completing the e-learning exercise.
- Ensure that pupils do not fulfill extra exercises that do not further develop their cognition.
- Principles of gamification has to be implemented – allowing pupils proceed earlier to a higher level based on actual results.

2.3.2 The standard passing through the exercises

The standard passing through the e-learning exercises is described by algorithm shown in the Figure 7. It is obvious that pupils have to pass all exercises of each Sub-set of the given set.

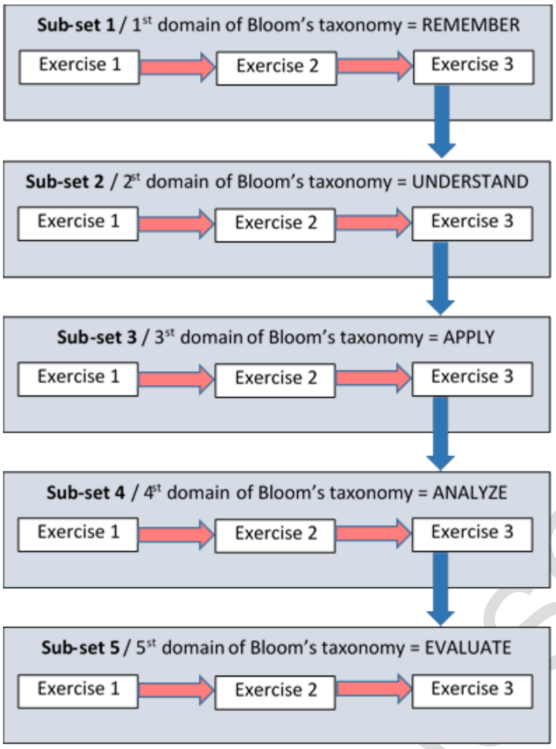

Figure 7. Algorithm of passing through e-learning exercise of control group of pupils

2.3.3 The adaptive passing through the exercises

The adaptive passing through the e-learning exercises of one set was adapted based on the requirement defined in the Section 2.3.1. The adaptation was made in LMS Moodle based on algorithm for passing through the one set of e-learning exercises. The difference from the standard passing is that the pupil has to pass at least one exercise of the first three Sub-sets of given set based on result of success rate *R* (the success rate will be defined in the Section 2.4) – the game principle is applied. If the pupil has success rate higher than 90% in the first exercise of the Sub-set, he does not pass other two exercises of given Sub-set and directly proceeds to higher Sub-set. Otherwise, he/she has to pass the second or the third exercise of the Sub-set. It is valid for the first three Sub-set, not for the fourth and fifth Sub-sets. All three exercises of the fourth and the fifth Sub-set have to be passed. The reason of this adaptation of the passing through exercise set is shortening of the exercise completion time (the completion time will be defined in the Section 2.4) for pupils who have success rate higher than 90%.

The algorithm of adapted passing through e-learning exercises fully fits to the learning analytics framework as well as the cognitive computing concept, because it evaluates pupils' success rate of e-learning exercises completion and decides to supply e-learning exercises so that the learning effectiveness increases (see Section 2.5).

Such adapted passing through the exercises would be more attractive for pupils, they would perceive the e-learning like game, and they would not be bored by completion of lower level exercises.

On the other hand, omission of the exercises can cause worse retention of the curriculum in the lower levels of the Bloom's taxonomy. It could cause worse success rate in higher level (mainly in the last level) of exercises. To obtain relevant data of curriculum retention, the all three exercises of the two last Sub-set has to be passed.

The algorithm of adaptive passing through e-learning exercises of one set is clearly shown in the Figure 8.

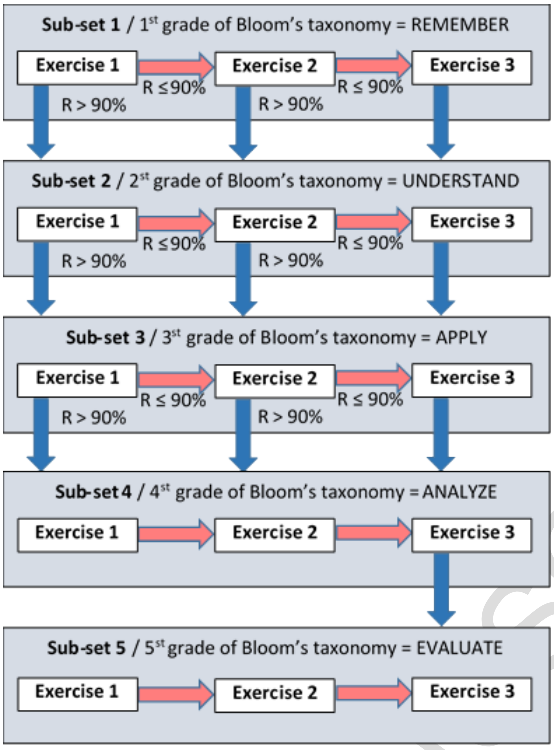

Figure 8. Algorithm of passing through e-learning exercise of experimental group of pupils

The learner's data of passing through the exercises sub-sets of the lowest three domains create learner's models of the adaptive e-learning. The models are discussed in the Section 4.1.1.

2.4 The Evaluation of the Exercise Completion

The development environment Hot Potatoes provides direct evaluation of the result of exercise completion for each pupil immediately. The main quantities of evaluation are:

- **Success rate *R*** – quantity in the range from 0% to 100% representing success of completed e-learning exercises;
- Time needed for exercise completion – **Completion time *t*.**

The quantity success rate acquires values from 0% to 100%. It represents success of completion of given e-learning exercises. The success rate is calculated directly by internal algorithm of Hot Potatoes system. The description of the algorithm exceeds beyond the scope of the paper. We only point out that the resulted value of success rate depends on following:

- The module, the exercise is based on;
- The weight of the result of a given "sub-exercise" – the final success rate of the exercise is calculated as weighted arithmetic mean of the "sub-exercises" results;
- The use of the help – if help is used the success rate is influenced and it can never be 100%;
- The number of attempts - a pupil has the option of multiple attempts. The pupil can decide if he or she is satisfied with the "wrong" result in the first attempt. If not, he or she can repeat the "sub-exercise"; if yes, he or she completes next one. The value of the success rate is influence and can no longer be the 100%.

The final value of the success rate of a given exercise for each of the pupils is recorded in LMS Moodle.
The time needed for exercise completion is measured in seconds. It is recorded in LMS Moodle as well.

2.5 Learning Effectiveness

The success rate R and the completion time t are the input quantities for the presented research (see Sections 4).
The pilot study (see Section 3.1 and 3.1.1) confirmed that the success rate R is not symmetrically distributed, i.e. it has not normal distribution and it cannot be statistically analyzed by standard parametric methods.
The completion time t can be normalized by transformation to log-normal distribution (see Section 3.1.2).
The success rate R has to be normalized by transformation to other quantity – the learning effectiveness E. The advantage of such transformation is that for the purpose of our research it is important to monitor not only the success rate R but also the exercise completion time t simultaneously (see Section 4).

Effectiveness (understood as productivity) is commonly defined as the relationship between the outcomes of an activity and the time needed to achieve these outcomes:

$$E = \frac{R}{t} \tag{1}$$

where *R* represents the outcomes of an activity and t represent the time needed to achieve these outcomes.
The effectiveness of the learning can be defined similarly as in the formula (1). The quantity *R* - outcomes in learning is represented by the success rate (in our research understood as the success rate *R* of completion of e-learning exercises - see above) and the completion time *t* - time needed for completion of the e-learning exercises.
The statistical analysis realized within pilot study confirmed that the success rate *R* of the exercise completion is independent of the completion time *t* (see Section 3.1.3) and therefore the quantities *R* and *t* can be used as input quantities to formula (1).
The minimum value of success rate in learning, i.e. minimum value of mastering the curriculum is commonly set as 50%, i.e. if pupil's success rate is less than 50%, the result is the pupil failed in his exercises. For the purpose of our research we set the effectiveness $E = 0$ for $R = 50\%$. Regarding this assumption, the formula (1) changed as follows:

$$E = \frac{R - 50}{t} \tag{2}$$

If the success rate *R* of completion of the exercise is less than 50% ($R < 50$] the effectiveness *E* is less than zero ($E < 0$). This result indicate that pupil does not master the curriculum.
Now, let's discuss the completion time. To avoid limit case for time $t = 0$ (the value of *E* is infinitely large in this case), the time t is extended by average time $\bar{t}$ needed for completion of a given e-learning exercise. The time $\bar{t}$ is calculated as average of completion times t_i of the given exercise.

The average time $\bar{t}$ is calculated as follows:

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_i \tag{3}$$

where *N* is number of the pupils.
The formula for calculation of the effectiveness *E* extended by average time $\bar{t}$ is in form:

$$E = \frac{R - 50}{t + \bar{t}} \tag{4}$$

The formula (4) was finally calibrated by factor $4\bar{t}$. The final formula for calculation of the effectiveness is:

$$E = 4\bar{t}\frac{R - 50}{t + \bar{t}}. \tag{5}$$

The examples of values of effectiveness *E* for significant values of success rate and completion time *t* are shown in the Table 1.

Table 1. Significant values of learning effectiveness *E*

R	*t*	*E*
100	$\bar{t}$	100
100	$(0,\bar{t})$	(200,100)
100	0 (limit case)	200 (maximum limit value)
50	any time	0
(50,100)	$\bar{t}$	(0,100)
<50	any time	<0

The **learning effectiveness** *E* is the quantity that the authors assumed meets the following requirements:

- eliminates the success rate *R* asymmetry,
- creates relation between success rate and completion time,
- has normal distribution,
- so can be statistically analyzed by standard parametric methods.

3. Materials and Methods

3.1 The Pilot Study

Within the pilot study, the authors focused on evaluation of the results of pupils of the third grade in subject Mathematics in academic year 2014/15. The results of a randomly selected set of e-learning exercises were statistically processed. The selected set consists of exercises for training the multiplication table up to hundred (examples of the exercises are shown above).
The pilot study was conducted to determine the behavior of the measured input quantities – the success rate R and the completion time t.

3.1.1 Success Rate

The main results of the statistical analysis - the number of the pupils with a success rate higher than 90% are summarized in the Table 2. The total number of the pupils was 30.

Table 2. The number and percentage of the pupils with success rate higher than 90% in pilot study, the total number of children is 30

Sub-set No Bloom's taxonomy domain	1 Remember	2 Understand	3 Apply	4 Analyze	5 Evaluate
Number of the pupils with success rate higher than 90 % (R > 90%)	18	11	11	15	13
Percentage of the pupils with success rate higher than 90 % (R > 90%)	60 %	37 %	37 %	50 %	43 %

The high percentage of pupils with a high success rate is given by setting of question difficulty in such a way that the "average pupil" answers correctly with 80% probability.
The results of the distributions of the success rate R in the form of box-and-whisker plot for all five Sub-sets of exercises are shown in the Figure 9.

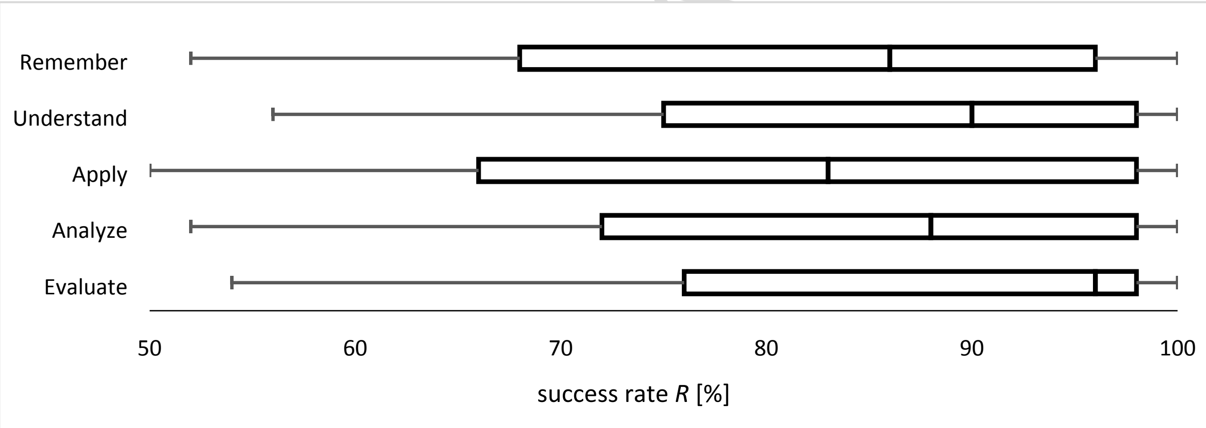

Figure 9. Box-and-whisker plot of the distribution of the success rate R for all five Sub-sets of exercises

The diagrams clearly show that frequency of the success rate R is not symmetrically distributed, i.e. it has not normal distribution (the success rates R have a significant asymmetry). This fact does not allow statistical analysis by standard parametric methods. The asymmetry is caused by the fact that the success rate R has statistical distribution derived from binomial distribution of questions in separate exercises. A question is replied either correctly or incorrectly (typical for binomial distribution). The set of the questions represents commutation of the binomial distributions. The other significant characteristic of the success rate R is high variability.

3.1.2 Completion Time

The results of the distributions of the completion time t in the form of box-and-whisker plot for all five Sub-sets of exercises are shown in the Figure 10.

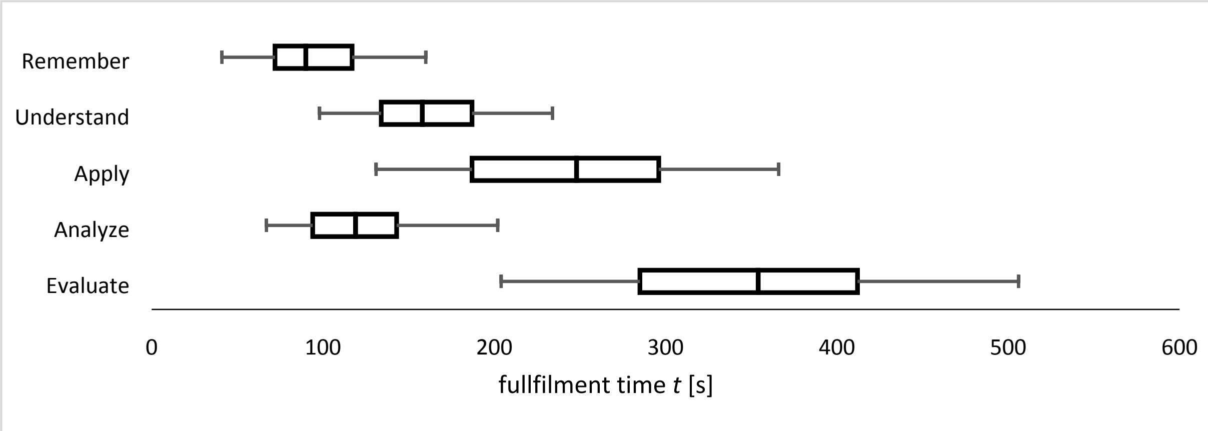

Figure 10. Box-and-whisker plot of the distribution of the completion time t for all five Sub-sets of exercises

The diagrams clearly show that the completion time t is not symmetrically distributed, i.e. they have not normal distribution. This fact does not allow statistical analysis by standard parametric methods.

The time can be symmetrized by transformation to a log-normal distribution. This method is commonly used in statistical analyzes of sport performance (running, swimming, skiing, ...). The examples of log-normal distributions of exercise completion time t are shown in the Figures 11 and 12. The log-normal distribution of time is evident from the chart on the Figure 11, while log-normal distribution of time is not evident from the chart on the Figure 12.

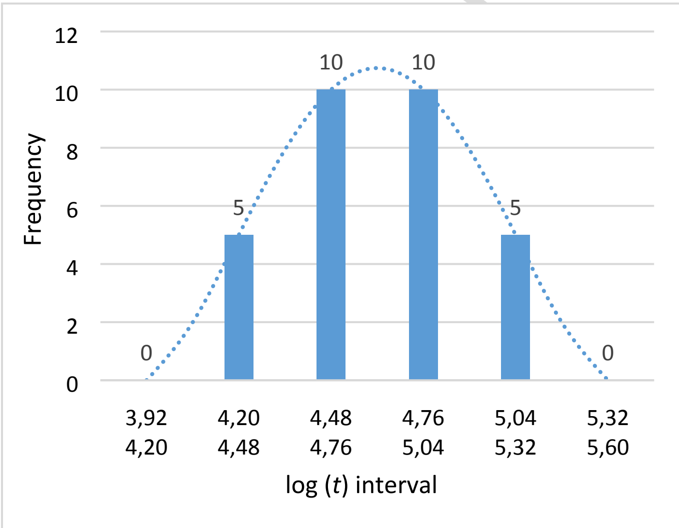

Figure 11. Example of evident log-normal distribution of time t

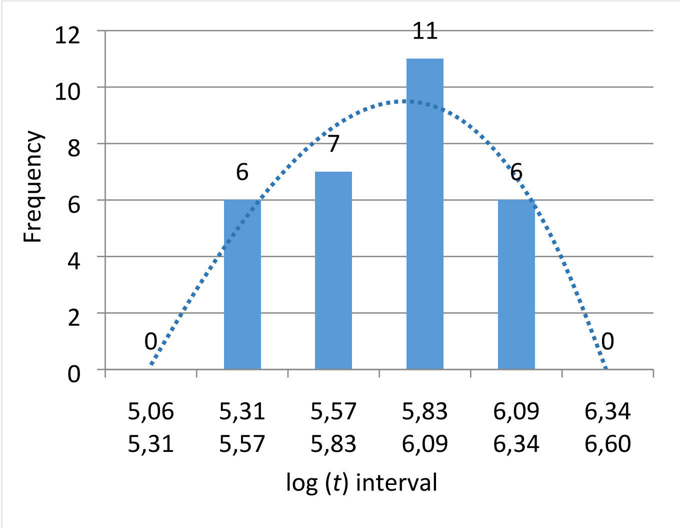

Figure 12. Example of not-evident log-normal distribution of time *t*

To confirm that the log(t) data correspond to random statistical sample of the normal distribution, the Kolmogorov-Smirnov normality test was used. The main quantity of the Kolmogorov-Smirnov statistic is difference D (EMS, 2001). The difference D is evaluated in our research.

All values of criteria D in all distribution intervals of log-normal time distribution for all five exercises' Sub-sets are less than the Kolmogorov-Smirnov critical limit D_{crit}. For total sample frequency N = 30 and significance level 5% is value of critical criterion D_{crit} = .242 – see Table 3.

Table 3. Values of criteria *D* in all distribution intervals of log-normal time distribution

	Difference *D*				
Distribution intervals of log(t)	Sub-set 1	Sub-set 2	Sub-set 3	Sub-set 4	Sub-set 5
⟨μ−3σ ; μ−2σ)	.027	.060	.006	.006	.006
⟨μ−2σ ; μ−σ)	.100	.067	.133	.100	.133
⟨μ−σ ; σ)	.191	.158	.091	.191	.125
⟨σ ; μ+σ)	.142	.109	.175	.142	.109
⟨μ+σ ; μ+2σ)	.067	.067	.067	.067	.067
⟨μ+2σ ; μ+3σ)	.006	.006	.006	.006	.006

The data presented in the Table 3 are taken from the initial calculations for time-frequency distribution and rounding the values to interval center. When it was found by this simplification that all measured data correspond the Kolmogorov-Smirnov normality test, the detailed tests "point by point" were carried out. The results of "point by point" meet the condition of Kolmogorov-Smirnov test. The tables with "point by point" test are not presented in the paper, because they are too large. The situation is similar in next statistical analysis.

The Kolmogorov-Smirnov normality test confirms that log (t) data correspond to the random statistical set of the normal distribution. The standard parametric methods for statistical analysis of the completion time logarithm can be used.

3.1.3 Correlation between Success Rate and Completion Time

Within statistical analysis, the correlation coefficients between success rates R and completion times t were calculated, as well. The values of correlation coefficients are summarized in the Table 4.

Table 4. Values of correlation coefficient between success rates *R* and completion times *t*

Sub-set No Bloom's taxonomy domain	1 Remember	2 Understand	3 Apply	4 Analyze	5 Evaluate
Correlation coefficient	− .02	− .04	− .08	− .30	− .48

The values of correlation coefficient confirm our assumption, the success rate and completion time are independent quantities. The result can be interpreted that some of the pupils can have high success rate in short completion time, while some of them spent long time and their success rate is low.

3.1.4 *Learning Effectiveness*

As already mentioned in Section 2.5, the **learning effectiveness *E*** is the quantity that the authors assumed meets the following requirements:

- eliminates the success rate R asymmetry,
- creates relation between success rate and completion time,
- has normal distribution,
- so can be statistically analyzed by standard parametric methods.

The learning effectiveness E is calculated based on formula (5) – see Section 2.5.

$$E = 4\bar{t}\frac{R-50}{t+\bar{t}}. \qquad (5)$$

where the time $\bar{t}$ is calculated as average of completion times t_i of the given exercise by all pupils in the third grade in previous academic year e.g. in academic year 2014/15 (the times t_i were recorded in LMS Moodle).
Note: The average time $\bar{t}$ represents the initial value calculated from the data from the previous academic year 2014/15. The research was realized in the third grade of academic year 2015/16.
The average time $\bar{t}$ is calculated based on formula (3):

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_i \qquad (3)$$

where $N = 48$ is number of the pupils in the third grade of the academic year 2014/15.

The distributions of learning effectiveness E of e-learning exercises completion of selected Sub-sets are shown in the Figures 13 (Sub-set 1) and 14 (Sub-set 5).

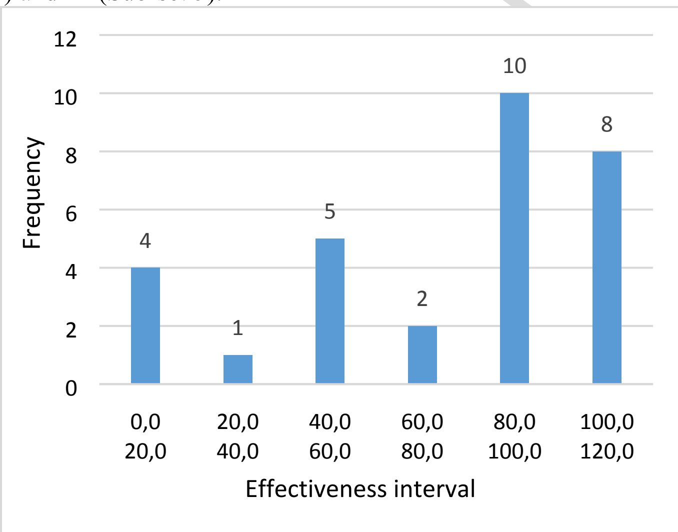

Figure 13. The distributions of learning effectiveness E of e-learning exercises completion of the Sub-set 1

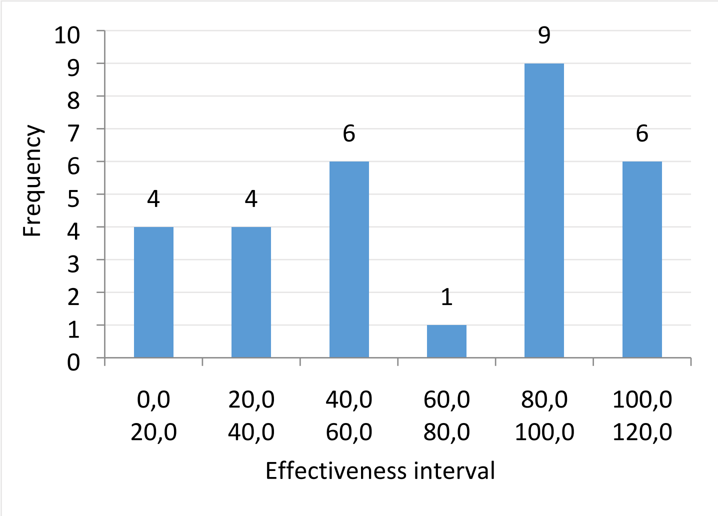

Figure 14. The distributions of learning effectiveness *E* of e-learning exercises completion of the Sub-set 5

To confirm that the learning effectiveness *E* data correspond to random statistical sample of the normal distribution, the Kolmogorov-Smirnov normality test was used. All values of criteria *D* in all distribution intervals of effectiveness distribution for all five exercises Sub-sets are significantly less than the Kolmogorov-Smirnov critical limit D_{crit}. For total sample frequency $N = 30$ with significance level 5% is value of critical criterion $D_{crit} = .242$ – see Table 5.

Table 5. Values of criteria *D* in all distribution intervals of effectiveness distribution

	Difference *D*				
Distribution intervals of *E*	Sub-set 1	Sub-set 2	Sub-set 3	Sub-set 4	Sub-set 5
< 20.0	.103	.069	.078	.014	.087
> 20.1; < 40.0	.069	.122	.143	.089	.129
> 40.1; < 60.0	.097	.117	.132	.148	.159
> 60.1; < 80.0	.044	.072	.071	.051	.034
> 80.1; < 100.0	.064	.037	.063	.035	.050
> 100.1;	.155	.087	.093	.121	.103

The Kolmogorov-Smirnov test of normality confirms that effectiveness data correspond to random statistical set of the normal distribution. The standard parametric methods for statistical analysis of the learning effectiveness *E* can be used. The results of the Kolmogorov-Smirnov test confirm that the formula (5) for the calculation of the learning effectiveness was set well and can be used for calculation in statistical analysis of pupils learning outputs.

3.2 The Research

The statistical evaluation of the use of e-learning exercise materials has been presented in the pilot study that was conducted in academic year 2014/15; see Section 3.1. The main result of the pilot study shows that there is a high percentage of pupils with the success rate higher than 90 % (it varies from 37% to 60%, see Table 2). It has been already mentioned in the Section 2.3 that completion of e-learning exercises of lower domains of Bloom's taxonomy would not develop cognitive thinking for solution of e-learning exercises of upper domains of Bloom's taxonomy. The time spent by solving "lower Bloom's exercises" would be "rather useless" for the pupils.

The aim of the presented research is to answer the research questions and confirm / reject the research hypothesis. The research questions and research hypothesis are listed in the next Sections.

3.2.1 The Research Questions

The authors defined the research questions:

- "Can be effectiveness of primary e-learning training increased by utilizing of elements of adaptive e-learning?"
- "Can any e-learning exercise of lower cognitive levels of Bloom's taxonomy be skipped without affecting the cognitive thinking for solution of the e-learning exercises on upper cognitive levels of Bloom's taxonomy?"

3.2.2 The Research Hypotheses

The research questions lead to the formulation of research hypotheses:

- "Skipping any e-learning exercise of lower cognitive domains of the Revised Bloom's Taxonomy does not negatively affect the completion time of solution of e-learning exercises of higher cognitive domains of Revised Bloom's taxonomy."
- "Skipping any e-learning exercise of lower cognitive domains of the Revised Bloom's Taxonomy does not negatively affect the effectiveness of e-learning exercise solutions of higher cognitive domains of Revised Bloom's taxonomy."

The domains *Remember, Understand* and *Apply* are understood as the lower domains of the Bloom's taxonomy in the presented research, while the domains Analyze and Evaluate are understood as the upper domains of the Bloom's taxonomy.
In the research, only the cognitive process dimension of Revised Bloom's taxonomy is realized.

3.2.3 Research Methodology

In order to confirm or reject the hypotheses the pedagogical research run.
Within the research the completion time (t_E) and effectiveness of completing e-learning exercises of the experimental group of pupils (E_E - see formula (5)) was compared with the completion time (t_C) and the total average effectiveness of completing e-learning exercises of the control group of pupils (E_C).
To conduct the research, two ways of doing the e-learning exercises were defined. The control group worked in a standard way based on the algorithm defined in Section 2.3.2, while the experimental group of pupils worked in an adaptive way based on the algorithm defined in Section 2.3.3.
The research was carried out in the Primary school in Úpice, the Czech Republic, in academic year 2015/16. The research was run in the third grades in subject Mathematics. Regarding the fact that the research was conducted on a small research sample - in the given school and in the given subject, the research results are presented in the form of a case study.
The two third-grades classes were in the school – 3A and 3B (in the age from 8 to 9). The class 3A consisted of 28 pupils while the class 3B consisted of 24 pupils, totally 52 pupils. All pupils of both classes had already worked with e-learning exercises in both the first as well as the second grades. They were experienced in the e-learning exercises.
Pupils of both classes were intentionally divided into two groups: the experimental group and the control group. The distribution of pupils was based on following rules:

- Both groups consisted of the same quantity of pupils – 26;
- The groups consisted of the pupils of similar distribution of evaluation rate in e-learning exercises in the second class in subject Mathematics;
- The groups consisted equally from pupils of 3A class and 3B class, so the teacher's personality interference with pupils' success was eliminated.

The curriculum of Mathematics of the third class also encompasses multiplication up to one hundred.
The confirmations / rejections of the hypothesis is given by statistical analysis of randomly selected set of exercises. The set of exercises was the same as in the pilot study (i.e. the set of exercises for training the multiplication table up to hundred).
As stated in the previous chapter, the Hot Potatoes exercises support standard full time learning. The e-learning has a supportive purpose.

4. Results and Discussion

To answer the research questions a pedagogical experiment were conducted. The experimental group of pupils did the set of e-learning exercises which were based on adaptive algorithm described in the previous paragraph. Before the main results relating to accepting and rejecting the hypothesis are presented, we will focus on the description of result data of the experimental group in exercise completion of lower Bloom's domains, namely Remember, Understand and Apply.
The learner's data on adaptive e-learning provide information on the passing through exercises lower Bloom's domains. Based on data analysis, the learner's models were created using learning analytics, see Section 4.1.1.

4.1 Summary of Experimental Group Research Results

4.1.1 The learner's models of adaptive e-learning

The number of exercises needed for completion of the Sub-sets of Bloom's domain Remember, Understand and Apply is shown in the Figure 15. Rather high percentage of pupils (it varies from 27% to 54%) passed the first exercise with success rate better than 90% and they were proceeded to the higher Sub-set directly. It confirms our assumption that the passing through e-learning of the experimental group of pupils differed from the passing through e-learning of the control group of pupils. The pupil passes through the lower Bloom's exercises faster when it is based on the adaptive algorithm. The Figure 15 shows charts representing distributions of the numbers of filled exercises by pupils of the experimental group in Bloom's domains Remember, Understand and Apply. Note that pupils in the control group had to fulfill all three exercises in all three lower Bloom's domains.

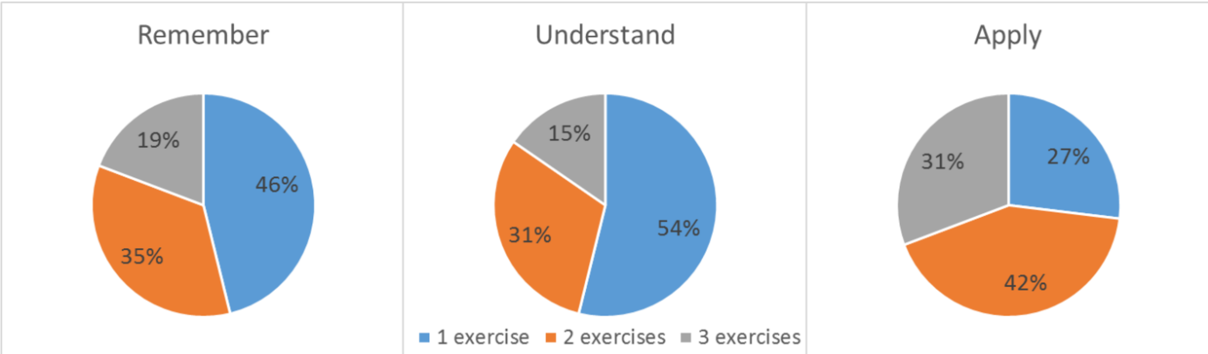

Figure 15. The number of exercises needed for completion of the first three Sub-sets

The detailed learner's data analysis of the experimental group of pupils provides the possibility for creation of learner's models of the adaptive e-learning. The individual models represent relative frequency of real passes through exercises of three lower Bloom's domains. In principle, there is in total 27 different learning models of the adaptive e-learning. Each of the three sub-set of exercises (*Remember*, *Understand*, *Apply*) can be described by numbers of 1 or 2 or 3 representing the number of exercises needed for the sub-set completion based on adaptive algorithm. The number of exercises required to complete the sub-sets is marked with the first letter of lower Bloom's domains, i.e. (R - U - A). The combinations of (R - U - A) represent the learner's models. There are theoretically 27 learner's models (1 - 1 - 1), (1 - 1 - 2), ..., (3 - 3 - 3). The learner's models occurring in our research are shown in the Table 6 (the models that did not occur in the research are not listed in the Table 6). The fastest passing through three sub-sets of lower Bloom's domains is represented by the learner's model (1 - 1 - 1), but this model does not occur in the research. On the other hand, the learner's model (3 - 3 - 3) is the slowest model with the total sum of exercise fulfilment 9 – this model occurs only once.

Table 6. The learner's models of presented primary adaptive e-learning

Label of Learning model	Remember R	Understand U	Apply A	Sum R + U + A	Relative frequency
A	1	1	2	4	11,5 %
B	1	1	3	5	11,5 %
C	1	2	1	4	7,7 %
D	1	2	3	6	7,7 %
E	1	3	1	5	3,8 %
F	1	3	2	6	3,8 %
G	2	1	1	4	7,7 %
H	2	1	2	5	15,4 %
I	2	2	2	6	3,8 %
J	2	2	3	7	3,8 %
K	2	3	3	8	3,8 %
L	3	1	2	6	7,7 %
M	3	2	1	6	7,7 %
N	3	3	3	9	3,8 %

It is clear from the Table 6 that the most common learner's models are models with the sum of R + U + A equal to 4, 5, or 6. The higher sums 7, 8 or 9 occur only rarely (totally only 11.5% of pupils are included in the higher sum).
The result confirms the effectiveness of the adaptive e-learning and reduction of total pupil's fulfilment time.
The models A and B (pupil needs to fulfill only 1 exercise in the first two sub-sets Remember and Understand, while he/she needs to fulfill 2 or 3 exercises in the sub-set Apply) confirm that the Apply domain is already quite demanding for primary school pupils and therefore pupil needs appropriate time and attention for practice.
Surprisingly, the model H has the highest relative frequency (pupil needs to fulfill only 1 exercise in the Understanding sub-set, while he/she needs to fulfill 2 exercises for the lowest Remember sub-set. The explanation of the unexpected anomaly requires another research that is beyond the scope of this paper.

The learner's models of proposed adaptive e-learning are examples of using learning analytics in primary education. The adaptive e-learning is based on the principle of the pupils' effort to complete the exercise sub-sets successfully and quickly. It represents gamification of learning.
The confirmation, that the use of presented adaptive e-learning increases the learning efficiency of e-learning in primary education, is presented in the following sections.

4.1.2 The Exercise Completion Time Comparison

It is clear that total average completion time needed for completing the exercises of the three lower Bloom's domains is shorter if adaptive passing through the exercises is applied. The assumption was confirmed by statistical analysis of the completion times – the total average completion times were calculated. The comparison of the total average completion times is shown in the Table 7. The average completion times of pupils from the pilot group are presented in the comprehensive Table 7.

Table 7. The comparison of the total average completion times

Sub-set	Remember	Understand	Apply
Average time of Pilot group $\bar{t}_P$	96 s	160 s	241 s
Average time of Control group $\bar{t}_C$	88 s	155 s	235 s
Average time of Experimental group $\bar{t}_E$	53 s	86 s	164 s
Rate $\frac{\bar{t}_C}{\bar{t}_E}$	1.66	1.80	1.43

As expected, the average times of pilot groups and control groups are almost identical. On the other hand, average times of experimental groups are shorter compared with average times of control (pilot) group. The rate $\frac{\bar{t}_C}{\bar{t}_E}$ clearly shows time acceleration. The acceleration varies from 1.43 to 1.80. Adaptive passing through the e-learning exercises causes the time shortening.

4.1.3 The Exercise Success Rate Comparison

Similarly, the comparison of average success rate completion of the exercises of lower three Bloom's domain is shown in the Table 8.

Table 8. The comparison of average success rate of exercise completion

Sub-set	Remember	Understand	Apply
Average success rate of Pilot group $\bar{R}_P$	87 %	83 %	82 %
Average success rate of Control group $\bar{R}_C$	86 %	88 %	80 %
Average success rate of Experimental group $\bar{R}_E$	83 %	85 %	80 %

Despite the different completion time between experimental and control (pilot) groups, the success rates are almost the same for experimental and control (pilot) group of pupils in corresponding domains of Bloom's taxonomy. This confirms the assumption that success rate is quantity inappropriate for statistical processing of the research hypothesis.

4.1.4 The Learning Effectiveness Comparison

The comparison of the average learning effectiveness of experimental and control (pilot) group of pupils is summarized in the Table 9.

Table 9. The comparison of the average learning effectiveness

Sub-set	Remember	Understand	Apply
Average effectiveness of Pilot group $\bar{E}_P$	74	68	65
Average effectiveness of Control group $\bar{E}_C$	73	73	64

Average effectiveness of Experimental group $\overline{E}_E$	99	104	78
Rate $\frac{\overline{E}_E}{\overline{E}_C}$	1.35	1.42	1.22

The average learning effectiveness in the experimental group of pupils is relatively high compared to the control (pilot) group of pupils; the learning effectiveness of the control and pilot groups is almost identical. The result confirms the assumption that the learning effectiveness *E* describes pupils learning outputs well.

4.2 The Hypotheses Confirmation

The main aim of the research is answering the research questions and confirmation or refutation of the hypotheses. The research questions were formulated above in previous paragraphs of the paper. In the following part of the paper, the last two questions will be answered. Let us recapitulate the questions:

- "Can be effectiveness of primary e-learning training increased by utilizing of elements of adaptive e-learning?"
- "Can any e-learning exercises of lower cognitive domains of Bloom's taxonomy be skipped without affecting cognitive thinking for solution of the e-learning exercises of upper cognitive domains of Bloom's taxonomy?"

The domains Remember, Understand and Apply were taken as the lower domains of the Bloom's taxonomy in the presented research, while the domains Analyze and Evaluate were taken as the upper domains of the Bloom's taxonomy. Under this assumption, the adaptive algorithm for passing through the exercises was implemented to LMS Moodle. The principle of the adaptation is that pupil can proceed from Sub-set of lower domain to the next Sub-set without completion of all three exercises of given Sub-set. It is valid for the Sub-sets corresponding to lower domains of the Bloom's taxonomy. The experimental group of pupils passes the e-learning adaptively, while control group of pupils passes all e-learning exercises.
The research questions lead to formulation of the research hypotheses – see previous paragraph.
These two common hypotheses were split to four sub-hypotheses:

- **H1**: "The skipping of any e-learning exercise of lower three cognitive domains of the Revised Bloom's Taxonomy does not negatively affect **the completion time** of solution of e-learning exercises of cognitive domain **Analyze** of Revised Bloom's taxonomy."
- **H2**: "The skipping of any e-learning exercise of lower three cognitive domains of the Revised Bloom's Taxonomy does not negatively affect **the completion time** of solution of e-learning exercises of cognitive domain **Evaluate** of Revised Bloom's taxonomy."
- **H3**: "The skipping of any e-learning exercise of lower three cognitive domains of the Revised Bloom's Taxonomy does not negatively affect **the effectiveness** of solution of e-learning exercises of cognitive domain **Analyze** of Revised Bloom's taxonomy."
- **H4**: "The skipping of any e-learning exercise of lower three cognitive domains of the Revised Bloom's Taxonomy does not negatively affect **the effectiveness** of solution of e-learning exercises of cognitive domain **Evaluate** of Revised Bloom's taxonomy."

While the sub-hypotheses H1, H2 concern the completion time *t*, the hypotheses H3, H4 concern the learning effectiveness *E*.

4.2.1 Sub-hypotheses H1, H2 Confirmation

The parametric methods of statistical analysis can be only used for data that correspond to a random statistical sample of the normal distribution. As already mentioned above in statistical analysis of the pilot study, the completion times *t* does not match to the normal distribution. The time was substituted by logarithms of time - log(*t*) that correspond to the log-normal distribution. Similarly, it was proved by a single-sample Kolmogorov–Smirnov normality test that logarithm of times of experimental group as well as control groups match to normal distribution for Sub-set 4 and Sub-set 5. The values of criteria *D* in all distribution intervals of log-normal time distribution are less than the Kolmogorov-Smirnov critical limit D_{crit}. For total sample frequency $N = 26$ and significance level 5% is value of critical criterion $D_{crit} = .259$ – see Table 10.

Table 10. The values of criteria *D* in all distribution intervals of log-normal time distribution

	Difference *D*			
Distribution intervals of log(*t*)	Control Sub-set 4	Experimental Sub-set 4	Control Sub-set 5	Experimental Sub-set 5
⟨μ−3σ ; μ−2σ)	.032	.006	.006	.006

⟨μ−2σ ; μ−σ)	.049	.164	.202	.126
⟨μ−σ ; σ)	.191	.191	.191	.115
⟨σ ; μ+σ)	.155	.193	.078	.116
⟨μ+σ ; μ+2σ)	.028	.067	.067	.067
⟨μ+2σ ; μ+3σ)	.006	.006	.006	.006

To confirm / refute hypotheses H1, H2 the two-sample Kolmogorov–Smirnov test were used to test difference D_2 between probability distributions of logarithms of the completion times of experimental group and logarithm of the completion time of control group of pupils.
The results are summarized in the Table 11.

Table 11. The values of D_2 between probability distributions of logarithms of the completion times of experimental group and logarithm of the completion time of control group of pupils

Distribution intervals of log(t)	Difference D_2 H1	H2
⟨μ−3σ ; μ−2σ)	.038	.000
⟨μ−2σ ; μ−σ)	.115	.077
⟨μ−σ ; σ)	.000	.077
⟨σ ; μ+σ)	.038	.038
⟨μ+σ ; μ+2σ)	.038	.000
⟨μ+2σ ; μ+3σ)	.000	.000

Critical limit D_{2crit} for total sample frequency N = 26 and significance level 5% is D_{2crit} = .361. All values of criteria D_2 in all distribution n intervals of log-normal time distributions are less than the Kolmogorov-Smirnov critical limit D_{2crit}. The difference D_2 between probability distributions of logarithms of the completion times of experimental group and logarithm of the completion time of control group of pupils is insignificant. **The hypotheses H1 and H2 are confirmed.**
Summarizing, the skipping of any e-learning exercises of the lower three cognitive domains of the Revised Bloom's Taxonomy does not affect negatively the completion time of solution of e-learning exercises of cognitive domains Analyze, Evaluate of Revised Bloom's taxonomy.

4.2.2 Sub-hypotheses H3, H4 Confirmation

The statistical analysis of the pilot study confirms the learning effectiveness E, calculated by the formula (5), correspond to random statistical sample of the normal distribution. Similarly, it was proved for learning effectiveness by single-sample Kolmogorov–Smirnov normality test that effectiveness of experimental group as well as control group match to normal distribution Sub-set 5 and Sub-set 6. All values of criteria D in all distribution intervals of effectiveness are less than the Kolmogorov-Smirnov critical limit D_{crit}. For total sample frequency N = 26 and significance level 5% is value of critical criterion D_{crit} = .259 – see Table 12.

Table 12. The values of criteria D in all distribution intervals of effectiveness distribution

Distribution intervals of E	Difference D Control Sub-set 4	Experimental Sub-set 4	Control Sub-set 5	Experimental Sub-set 5
< 20.0	.028	.000	.109	.056
> 20.1; < 40.0	.128	.035	.183	.108
> 40.1; < 60.0	.226	.007	.114	.073
> 60.1; < 80.0	.038	.147	.011	.010
> 80.1; < 100.0	.016	.199	.048	.127
> 100.1; < 120.0	.102	.146	.077	.109
> 120.1; < 140.0	.000	.051	.059	.000
> 140.1	.000	.006	.018	.000

To confirm / refute hypotheses H3, H4 the two-sample Kolmogorov–Smirnov test were used to test difference D_2 between probability distributions of effectiveness of experimental group and effectiveness of control group of pupils.
The results are summarized in the Table 13.

Table 13. The values of D_2 between probability distributions of learning effectiveness of experimental group and learning effectiveness of control group of pupils

Distribution intervals of E	Difference D_2	
	H3	H4
< 20.0	.077	.077
> 20.1; < 40.0	.231	.115
> 40.1; < 60.0	.250	.077
> 60.1; < 80.0	.269	.000
> 80.1; < 100.0	.115	.115
> 100.1; < 120.0	.077	.077
> 120.1; < 140.0	.000	.000
> 140.1	.000	.000

Critical limit D_{2crit} for total sample frequency N = 26 and significance level 5% is D_{2crit} = .361. All values of criteria D_2 in all distribution intervals of effectiveness distributions are less than the Kolmogorov-Smirnov critical limit D_{2crit}. The difference D_2 between probability distributions of effectiveness of experimental group and effectiveness of control group of pupils is insignificant. **The hypotheses H3 and H4 are confirmed.**

4.3 Discussion

The paper describes the possibilities of implementation of adaptive elements into e-learning material in primary education. We tried to find answers to the questions whether and in what ways the elements of adaptive e-learning might be implemented into the e-learning materials and whether adaptive e-learning brings any measurable benefits compared to the traditional e-learning.

The presented research was done with a limited sample of the pupils. The limited number of participants was determined by the discussed in Research Methodology, see Section 3.2.3. The emphasis was placed on the research run in the real environment of the school. Laboratory conditions could distort the results of the research. Authors realize that research results need to be verified on a larger sample of pupils, or expand to other subjects. However, the choice of the mathematics for the presented research appears to be appropriate and fitting because it is possible to distinguish the individual cognitive categories of the Bloom Taxonomy.

During implementation of the e-learning system at primary school, the authors noticed that pupil learning is relatively ineffective. Pupils were wasting time. The learning effectiveness decreases with routine completion of simple exercises. Pupils thus lose motivation. The authors decided to use the concept of learning analytics. According to the 1st International Conference on Learning Analytics and Knowledge, “learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.” (Siemens, & Long, 2011). The proposed adaptive primary e-learning algorithm fully fits into the learning analytics framework. The proposed algorithm evaluates pupils' success rate of e-learning exercises completion. Based on the analysis of these data, the algorithm decides to go through e-learning exercises so that the learning effectiveness is increased.

The proposed adaptive primary e-learning algorithm creates learner’s models that are presented and discussed in the Section 4.1.1. The learner’s models of adaptive e-learning.

Firstly, the researchers defined learning effectiveness as a quantity describing the results of pupil's completion of the exercises. The authors are aware of the fact that not only the success rate of the exercises completion plays an important role in the assessment, but also the time necessary for the completion of the exercise. A pupil who manages to complete exercise on 100% in longer time period used his learning potential in a worse way than a pupil who completed the exercise on 100% in shorter time period. The quantity of effectiveness, as defined by the authors, suitably expresses pupil's results, which was confirmed by the research.

It is important to stress that the e-learning itself is not spread in the frame of primary education as much as it is on universities or high schools. In order to answer the research questions authors used e-learning implemented in the Primary School in Úpice. The advantage of e-learning materials in the school was the fact that the materials created by means of author system Hot Potatoes by the teachers of the given school strictly followed Bloom´s Taxonomy of Cognitive Domains (see Section 2.2). The authors used this reality within the scope of the presented research. They were analyzing whether skipping of exercises developing the lower cognitive domains of the Revised Bloom’s Taxonomy would influence the pupil's results in completing the higher stages of the taxonomy.

The implementation of the adaptive algorithm, designed by the authors of the paper, into e-learning (see Section 2.3.3) allows respecting individual learning style and pupil's work pace. Observation of the experimental group pupils allowed tracing important moments emerging from the implementation of adaptive elements into the e-learning material structure. The implementation of adaptive e-learning into the education process allowed

respecting pupil's individual work pace. The gifted pupils were able to work faster – they progressed faster into higher levels of the taxonomy. The less gifted pupils worked slower. The pupils usually work on the computer with keen interest and strong desire. The lesson utilizing adaptive e-learning is more entertaining and interesting for them. The dialogues with teachers regarding the implementation of adaptive e-learning into the education process confirmed the presumptions that the elements of e-learning exercise adaptability enriched the education, livened teaching up, were more entertaining for pupils and the gifted pupils were not bored because of faster progress rate. The teachers highly appraised assessment by means of effectiveness, which allowed them to take into consideration pupil's work pace. Furthermore, they suggested that the adaptive e-learning should be enhanced by pedagogical game agent. The importance of the element, which strengthens the adaptive e-learning gamification, is addressed by Nunes, Bittencourt, Isotani and Jaques (2016).
The goal of cognitive computing is to simulate human brain activity and help improve human decision making (Kelly, 2015; Cerna, 2017). The goal of our adaptive e-learning algorithm is to make decision instead of a pupil to skip the routine practice of tasks at the lower level of the Bloom Taxonomy. This leads to an increase in learning effectiveness, as research results have confirmed. Our earlier observations have revealed that there were two groups of pupils. A part of the pupils (gifted or with effective learning habits) would skip these tasks if the original (non-adaptive) e-learning offered this possibility. The other group of primary school pupils is careful and studious and these pupils would waste time by repeating simple problems. The proposed adaptive algorithm erases the differences between these two groups. The proposed adaptive algorithm meets the typical features of cognitive systems:

- adaptivity: Our proposed adaptive algorithm is based on real time data.
- interactivity: It is ensured by implementing the adaptive algorithm itself into the Hot Potatoes environment.
- contextuality: it is realized by the pupil's passing through a comprehensive series of e-learning exercises. The adaptive algorithm takes into account pupil's individuality.

Although the research was conducted on small research sample, it was possible to test the results by means of standard statistical methods, which significantly supported their credibility. It was proven that the skipping of any e-learning exercise of the lower three cognitive domains of the Revised Bloom’s Taxonomy does not affect negatively the effectiveness of solution of e-learning exercises of cognitive domains Analyze, Evaluate of Revised Bloom’s taxonomy. This is confirmed by the statistically processed results of the experiment (see Section 4.2.1 and 4.2.2). As seen from Tables 11 and 13, the Kolmogorov-Smirnov critical value is .361 and it must not be exceeded by any of the sub-values for particular intervals. This is accomplished, because the highest values for the sub-hypotheses are as follows: H1: .115, H2: .077, H3: .269, and for H4: .115. Partial sub-hypotheses are therefore verified with a high degree of certainty. The validity of the cumulative major research hypotheses is based on the validity of the sub-hypotheses.
The comparison of the total set average completion time $\bar{t}_{set}$ (meaning the average time needed for completing exercise of complete set), average set success rate $\bar{R}_{set}$ (meaning the average success rate of complete set) and average set effectiveness $\bar{E}_{set}$ (meaning the average effectiveness of complete set) is summarized in the Table 14.

Table 14. The comparison of the total set average completion time $\bar{t}_{set}$, average set success rate $\bar{R}_{set}$ and average set effectiveness $\bar{E}_{set}$

	$\bar{t}_{set}$	$\bar{R}_{set}$	$\bar{E}_{set}$
Control group of pupils	926 s	83 %	70
Experimental group of pupils	754 s	86 %	89

The comparison confirms shortening of the total average time, conservation of the average value of success rate and increase of the average value of effectiveness.
The hypotheses confirmation answers the research questions. The e-learning exercises of lower cognitive domains of Bloom’s taxonomy can be skipped without affect for solution of exercises of upper cognitive domains. The pupils do not have to fulfill all e-learning exercise of all domains of the Bloom’s taxonomy. The effectiveness of primary e-learning training can be increased by utilization of features of adaptive e-learning. Adaptive e-learning can be implemented in form of Adaptive Learning Game Design (ALGAE). Such adapted passing through the exercises is for pupil more attractive. They perceive the e-learning like game, they are not bored by completion of lower level exercises. Simultaneously the presented results of the research confirm that omission of the exercises do not cause worse retention of the curriculum in all levels of the Bloom’s taxonomy. The presented adaptive primary e-learning can support eventful work, activity and high workflow of pupils. The research results confirm that concept of learning analytics can be implemented to primary school e-learning.

It is important to stress that not only the e-learning, but also the adaptive e-learning has irreplaceable position in the lowest education level, which is documented by the study of Drigas, Kokkalia and Lytras (2015).
Finally, despite the positive effect of the primary adaptive e-learning, it must be emphasized that the primary e-learning has only supportive character in primary education.
The issue of using e-learning in primary education is still scarcely researched and discussed, therefore the paper incontrovertibly brings new insights into the field of learning innovation. An innovative approach is undoubtedly the introduction of adaptability elements into primary e-learning, which brings new knowledge also in the area of cognitive computing in learning systems.

5. Conclusion and Future Work

The authors of the paper realize certain weaknesses given partly by the triviality of chosen adaptive e-learning algorithm and partly by the fact that the research was done with a limited sample – on a selected set of exercises. Despite the fact that the research results confirm the increase in the learning effectiveness, the authors realize that the research has to be extended. The authors plan realization of a similar research in all subjects, where e-learning exercises are implemented in and across all primary grades.
The authors are intending to deal with further improvement of the primary e-learning adaptability. The motivation for further research is for example the study (Dascalu, Bodea, Lytras, Ordonez de Pablos, & Burlacua, 2014), in which the authors suggest a way, how by means of adaptive e-learning to create optimal groups for collaborative learning, where individual members have different tasks. This approach is based on evolutionary algorithm - Particle Swarm Optimization. Despite the fact that the aforementioned study was related to adult education, we intend to prove that e-learning in primary education level can be developed in similar way. The especially important fact will be that individual pupils will work in a group, thus eliminating the negative phenomenon of e-learning like the lack of physical contact with their classmates.
Current adaptive e-learning will be easily accessible and more motivating for pupils by its adaptation for mobile devices (smart phones, tablets). The authors suppose that the environment innovation will be accomplished according to the recommendations presented in the study of Miranda, Marzano and Lytras (2017). Their study considers the shift from kindergarten age category to the age category we chose, i.e. children from 6-11 years old.
We plan in our future work not only use the learning management system in pupils learning mentioned above but also coordination of teacher's leadership by the same way. Possibilities and experiences from the implementation of teacher's practical training in the use of distance learning are discussed e.g. in paper of Michalik and Toman (2013).
The authors recommend to the policy makers of educational systems in the Czech Republic to incorporate adaptive algorithms based on the principles of learning analytics into teaching of various subjects within the national project “Strategy of Digital Education”.
The authors also recommend the implementation of learning analytics in the form of adaptive e-learning not only at primary school but also in higher education. It can be expected that learning effectiveness would increase at higher levels of school as well. The research issues of the impact of learning analytics and cognitive computing to learning effectiveness is one of the research goals of Ph.D. studies "ICT in Education" accredited at the University of Hradec Kralove.

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ACKNOWLEDGEMENT

The research was supported by Specific research project of Faculty of Education University of Hradec Kralove, and Specific research project of Faculty of Science, University of Hradec Kralove.

Highlights:

- Adaptive e-learning (AE) application in primary school education were studied.
- Algorithm for primary AE based on concept of learning analytics was proposed.
- Adaptive algorithm of primary AE meets the typical features of cognitive computing.
- Learning effectiveness (LE) was clearly and exactly defined.
- It was confirmed that the LE of primary e-learning increases by utilization of AE.