Expert Systems With Applications 90 (2017) 414–426

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

# A comprehensive adaptive system for e-learning of foreign languages

Vladimir Bradac, Bogdan Walek*

*Department of Informatics and Computers, University of Ostrava, Ostrava, Czech Republic*

A R T I C L E I N F O

*Article history:*
Received 18 February 2017
Revised 8 August 2017
Accepted 9 August 2017
Available online 16 August 2017

*Keywords:*
Intelligent tutoring system
Expert system
Fuzzy logic
Adaptive system
E-learning
Personalised education
English as a second language

A B S T R A C T

The article presents a proposal, design and implementation of a new approach to adaptive e-learning systems. First, a proposal of a model is presented. This model aims at introducing adaptivity to current e-learning systems, which are rigid and limited in offering a truly personalised learning to individual students. Many of current e-learning systems enable personalised learning. However, in this paper, there is a new, innovative approach proposed for an adaptive personalised e-learning system. The primary area of our research is English as a second language (ESL). Adaptivity in our view is considered as an ability of the system to adapt to student's knowledge and characteristics. This pedagogical perspective requires introduction of such processes that enable to work the pedagogical aspects of teaching/learning. The required processes are of informatics nature. The proposed model was subsequently designed into a real application. Finally, the application was implemented and verified on a real data set. The results are also provided.



## 1. Introduction

E-learning users have already got used to take the advantage of computer-based education, primarily if it concerns foreign languages (Bos & van de Plassche, 1994). Language education using e-learning systems is currently very popular, this was of learning is described in detail in Andrews and Haythornthwaite (2007). Thanks to huge expansion of social networks, language education is also possible online using such networks. Language education through social networks is described in Lin, Warschauer, and Blake (2016). One of possible approaches to online testing is described in El-Hmoudova, Milkova, and Garant (2012). As it was proved by Rudak et al. (2012), languages can be taught and learnt using an e-learning form, although there exist certain limitations. The results are subsequently also quite "limited" and as Murphy and McTear (1997) point out, e-learning of foreign languages lags behind providing a flexible feedback and personalised approach. Currently, there is a number of intelligent techniques for personalisation in e-learning systems (Klasnja-Milicevic, Vesin, Ivanovic, Budimac, & Jain, 2016). There are also various strategies for creating and implementations of intelligent tutoring e-learning systems, which are closely described in book by Woolf (2010).

Although this idea appeared thirty years ago, the computer-based education, primarily in the form of Intelligent Tutoring Systems (ITS) have not achieved its full potential yet (Ferster, 2014). Over the time, this resulted in the development of various systems (mostly as an LMS – Learning Management System) which would remove such negatives. Primarily, it concerns the English language as a recognised communication, publication and scientific language all over the world. English has already become a so-called lingua franca. Research in this field can be categorised into the areas of its research and methodology focus:

- adjusting of existing LMSs with so far unused pedagogical approaches
- change of existing LMSs from the technical point of view, thus enabling to implement necessary functionalities to introduce new, so far impossible processes
- adaptivity

## 2. Current state

### *2.1. Systems for more effective foreign language education and its optimization*

Currently, there are several approaches to optimise and make foreign language education through e-learning more effective. Such approaches will be mentioned in the text below. The first one is optimization of foreign language education in relation to learning styles. The objective of such an approach is to detect perception preferences of a student according to the VARK methodology and a subsequent offer of a suitable modification of the course according to the detected preferences. Although this approach is called by the authors called adaptive, in fact, it is rather only a one-time

* Corresponding author.
*E-mail addresses:* vladimir.bradac@osu.cz (V. Bradac), bogdan.walek@osu.cz (B. Walek).

http://dx.doi.org/10.1016/j.eswa.2017.08.019

categorisation of the student into an appropriate course setting (Jurickova, 2012).

Despite dated at the beginning of this millennium, the following approach is still a representative of current efforts. It concerns "The Passive Voice Tutor" (Virvou, 2001), which is a system for education of the passive voice for Greek students based on the idea of an ITS. Based on student's answers in the area of the passive voice, the system provides the student with appropriate feedback and adapts to continuous results. This system enables automation of the learning process, primarily in a form of testing and identification of student's weak areas with subsequent effort to eliminate them (Etienne, 1987). Unfortunately, this system is usable for education of the passive voice only, which is only a very small part of language education.

Authors (Nedbalova & Kostolanyova, 2015) describe a general model and a theory of adaptive eLearning using learning styles from the perspective of university teachers. It also demonstrates hard facts of the research in the field of language learning.

### *2.2. Adaptivity, related works*

Adaptivity of a system means system capability to adapt to changing input information, which the system reacts to with an appropriate change. Traditional LMS systems, in general, do not offer the possibility to adapt to users' needs in such an extent that would qualify them to be called adaptive. A course in such a system acts as a single module with no possibility to branch it, thus students are forced to proceed according to strictly defined milestones. A traditional LMS system is primarily used for course administration, control, testing and evaluating of students, and a communication tool between a student and a tutor. All of those activities are permanently carried out under tutor's supervision, who guides the student through the course to achieve the best possible result. It is fully up to the teacher to recommend suitable materials or methods, which might be often very difficult as the tutor does not have personal contact with the students. To analyse individual students according to which materials they have studied and results they have achieved would be very time consuming, if not impossible.

Unlike a traditional system, there have been efforts to produce adaptive systems, primarily adaptation to student's learning styles, e.g. in Truong (2016). This work summarises various approaches to learning styles and their classification. In order to support learning styles with adaptivity, a representative that has been tested in real is called Virtual Teacher. It is a model example of an adaptive educational system which carries elements of dynamic adaptive education (Kostolanyova, 2012). However this system also considerably differ from the system proposed in our research. The most significant difference is the process of identification of student's knowledge, work with his learning style or creation of a predefined models of virtual students (which is not the case in our system, where each student is a unique entity not assigned to any category.

Another approach is an intelligent tutoring system, which suggests suitable content based on feedback from students by questionnaires and their preferences (Tzouveli, Mylonas, & Kollias, 2008).

Another mentioned examples of approaches for personalised learning can be found in Li, Chang, Chu, and Tsai (2012) or automated learning assessment (Sánchez-Torrubia, Torres-Blanc, & Trivino, 2012) or Wang (2014).

All of the above-mentioned systems or approaches have one big drawback – they do not integrate all necessary elements of an adaptive system at full extent or they do not prove to be usable as a versatile system in other areas.

Approaches to integrate learning styles and a proposal of an adaptive e-learning system is well described in Truong (2016).

Our approach is thus significantly different, see next chapters, where it is described in detail.

## 3. Motivation and objectives

The main motivation of our work was to propose a new approach for the creation of an adaptive e-learning system for language education. The main aspects of the proposed approach are as follows:

- Detection of student's sensory preferences (not a learning style), which enables to create an idea of a suitable form of the learning content for the given student (for more details see Bradac, 2013).
- Use of an expert system to test student's level of knowledge in order to find out the need to study individual categories of the test (for more details see Bradac, 2014 and Bradac, Walek, Klimes, & Farana, 2014).
- Displaying suitable study materials for individual categories based on the assessed need to study, sensory preferences, and overall time of study (for more details see Walek & Bradac (2015)).
- Adaptation of the learning content based on student's initial knowledge, sensory preferences as well as results during the studies in order to ensure optimal progress.
- Each student has a personalised study variant, i.e. there are no pre-defined student's models which would serve for grouping of the tested students.

It is highly important to focus on the pedagogical part of the studies, primarily as gathering information on student's learning style, perception of information (sensory preferences), and initial level of knowledge. Such information is used to adapt the learning process from its very beginning to its end. It is necessary to adapt current e-learning courses that are rigid and the same for all students towards individual learning needs of students.

The technical aspect is also in the centre of interest in proposing a new methodology of adaptation in e-learning. Our approach stems from a decision-making model under indeterminacy, which means integrating such processes into LMSs that will make e-learning more effective in areas of adapting the content of the course (personalisation of the learning content) and the form of the content (personalisation of the learning content to sensory preferences). This is done based on identification of student's knowledge and its assessment, which leads to the creation of a personalised study plan for each student. Identification of student's knowledge, its assessment, and the creation of a personalised study plan will be performed based on previous experience with language education using a fuzzy-oriented expert system containing a knowledge based of IF-THEN rules. Those rules were created by an expert on language education.

Such a comprehensive model of an adaptive e-learning system should integrate both areas into several follow-up steps in a way that enables to adapt the whole learning process. Processing information from a student, a teacher, and an expert will lead to considerably higher effectivity and user-friendly way of teaching/learning languages using e-learning.

Our practical objective is to verify whether the proposed model as a whole is usable in a real process of e-learning of languages: (a) if the proposed parts of the model, i.e. IF-THEN rules, didactic test and its analysis, sensory preferences detection, etc. are functional, (b) if individual processes of identification, assessment, and planning are in accordance with the methodology of language e-learning and lead to the desired goals/results in a given e-learning course.

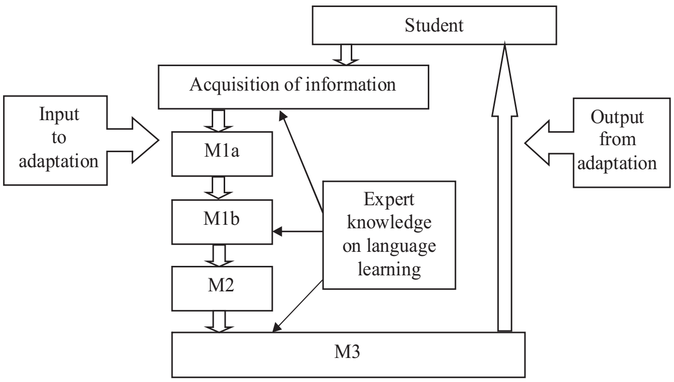


**Fig. 1.** Block scheme of the proposed model.

### 3.1. Expert systems for adaptivity

Expert systems in their various forms belong to most spread tools of artificial intelligence (Liao, 2005; Zadeh, 1983). No matter the way how information is stored in a knowledge base of an expert system, it must always be acquired from an expert. The most natural and operative expression of such knowledge is a natural language. In addition, it has been proved by practical usage that the most effective form of expressing human knowledge are IF-THEN rules (Novak, Perfilieva, & Dvorak, 2016; Novak and Lehmke, 2006; Pokorny, 2012; Zadeh, 1988). Expert systems enable to use expert knowledge – in our case knowledge of an expert in the area of language learning (one of the authors) – in order to achieve such a situation when it will be possible to assess student's knowledge and create a study plan for each student according to their needs. If it were done by an expert-human manually, it would be, in fact, impossible or extremely demanding, thus undesired and ineffective for a teacher. Substituting a human element by an expert system, which holds the human knowledge of a given area, is one of the steps how to move e-learning systems towards adaptivity.

This area of research has been active for many years. It primarily concerns hypermedia and educational systems in Brusilovski (1996), who is considered one of the founders of adaptive systems, and mainly (Brusilovski & Millán, 2007). Kakoty in Kakoty et al. (2012) deals with the use of an expert system to assess the expertise of a student based on their activity in an e-learning system. Verdú in Verdú, Verdú, Regueras, de Castro, and García (2012) uses a fuzzy-oriented expert system to automatically classify questions in an e-learning system. El Alami in El Alami et al. (2011) uses a fuzzy-oriented expert system to assess student's mistakes. Yildiz in Yildiz et al. (2013) is the last but not least representative of the use of an expert system in the e-learning environment.

The analysis of the above-mentioned systems reveals that a compact and comprehensive system combining elements necessary for modern e-learning - such as use of learning styles/sensory preferences, identification knowledge of individual categories of the language, determination of suitable learning objects, creation of a personalised study plan – that would be developed, tested and used in practice cannot be found.

## 4. Description of the model

In this chapter, we propose an adaptive model for the educational process. The proposed model takes ground from the model of decision-making in Klimes (2011). Our proposed model is schematically depicted in Fig. 1:

The proposed model includes the following basic steps (processes), which will be further described in the following subchapters:

- Acquisition of information about student – student's data on areas concerned in the decision-making.
- M1a - acquisition of information about student's sensory preferences and their evaluation.
- M1b - acquisition of information about student's level of knowledge and its evaluation.
- M2 – defining the objectives for the student based on the analysed information.
- M3 – process of finding a study variant for the given student.

### 4.1. Acquisition of information about student

The input information is information provided by a student before the learning process starts as well as stored in the system as default one. The input into the expert system is the didactic test. The test depends on the registered course. The questionnaire of sensory preferences is only one as it is standardised. It is not dependent on any subject, no other variables depend on it.

The process consists of the following steps:

1. Identification of the student and reading student's personal data
2. Reading student's registered course for the given semester
3. Reading categories (means one learning unit), one category is one learning objective (e. g. in LMS Moodle)
4. Reading the didactic test for acquisition of student's knowledge of individual categories, incl. questions and correct answers; each question is assigned to particular category (is included in particular learning unit)

### 4.2. Process M1a

In this process, the questionnaire of sensory preferences is read. Having it completed, it is evaluated for the frequency of individual modalities, it concerns V, A, R, K modalities (visual auditive, read/write, kinaesthetic). Typically, after evaluation, one strongest modality is found out with a combination of lower frequency of others (e.g. V means that the most frequent modality in the answers was visual).

The process consists of the following steps:

1. Reading the questionnaire of sensory preferences.
2. Completion of the questionnaire and its automatic evaluation.
3. Reading the main sensory preference of the student.

Calculation of the sensory preferences frequency is done as follows:

$V_{\%}$=[Frequency$V$/(Frequency$V$+Frequency$A$+Frequency$R$+Frequency$K$)]*100
$A_{\%}$=[Frequency$A$/(Frequency$V$+Frequency$A$+Frequency$R$+Frequency$K$)]*100
$R_{\%}$=[Frequency$R$/(Frequency$V$+Frequency$A$+Frequency$R$+Frequency$K$)]*100
$K_{\%}$=[Frequency$K$/(Frequency$V$+Frequency$A$+Frequency$R$+Frequency$K$)]*100

The output for each student are values: $V_{\%}$, $A_{\%}$, $R_{\%}$, $K_{\%}$.

### 4.3. Process M1b

In this process, the didactic test is read. Each question contains several possible answers, multiple choice. The question is assigned to a particular category (students do not see it). Each question also carries a different weight according to its difficulty within the category. Each category also carries a different weight according to its importance within all categories in the test. An example of a question is depicted in Fig. 2:

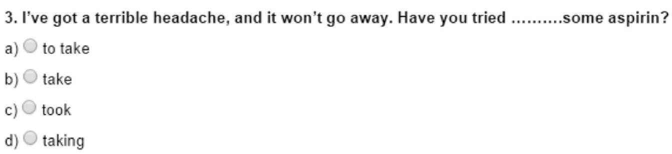


**Fig. 2.** Example of a question from the didactic test.

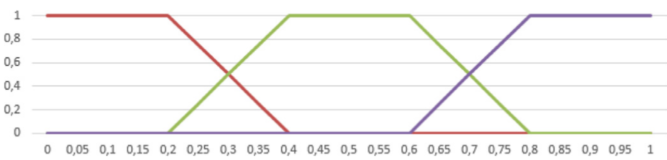


**Fig. 3.** Membership functions for V1.

During completion of the test, the time for answering each question is measured by the system automatically. This information is also important for the final evaluation. Having completed the test, the test is automatically evaluated (evaluation of correct answers) and the following steps are carried out:

(1) First, it is found out if the student has met the minimum knowledge level to be allowed to enter the registered course. The test is assessed as a whole:
$(Q_i + Q_j + \ldots + Q_n) \geq Q_{total} * 0.4$ (at least 40% in test results)
If the minimum requirements are met, step two is initialised. If not, the student is alerted about the result and a recommendation to register another course (i.e. lower level) is displayed.
(2) In this step, each category included in the test is assessed separately. This process uses a fuzzy-logic expert system and a knowledge base containing a set of created IF-THEN rules. The expert system assesses the read input data V1-V4 and provides the output V5.

The input linguistic values in the expert system are:

- V1 – number of correct answers within the category
- V2 – weight of correct answers within the category
- V3 – importance of the category for further studies
- V4 – time spent over answers of the category

The output linguistic variable from the expert system is:

- V5 – need of further studies of the given category

An example of IF-THEN rules of the expert system (ES):

1. IF (V1 is small) and (V2 is small) and (V3 is very small) and (V4 is small) THEN (V5 is small)
2. IF (V1 is medium) and (V2 is small) and (V3 is very small) and (V4 is small) THEN (V5 is very small)
3. IF (V1 is big) and (V2 is small) and (V3i s very small) and (V4 is small) THEN (V5 is ex small)
4. IF (V1 is small) and (V2 is medium) and (V3 is very small) and (V4 is small) THEN (V5 is small)
5. IF (V1 is medium) and (V2 is medium) and (V3 is very small) and (V4 is small) THEN (V5 is very small)
6. IF (V1 is medium) and (V2 is big) and (V3 is very small) and (V4 is small) THEN (V5 is ex small)
7. IF (V1 is big) and (V2 is medium) and (V2 is very small) and (V4 is small) THEN (V5 is ex small)
8. IF (V1 is big) and (V2 is big) and (V3 is very small) and (V4 is small) THEN (V5 is ex small)

The knowledge base of the ES includes 135 rules.

Fig. 3 shows the membership functions for V1 variable. The red line marks the linguistic expression *small*, other expressions are *medium*, *big*. Fig. 4 shows the membership functions for V5 variable.

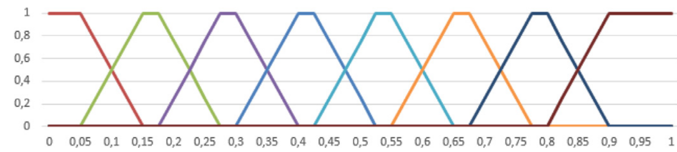


**Fig. 4.** Membership functions for V5.

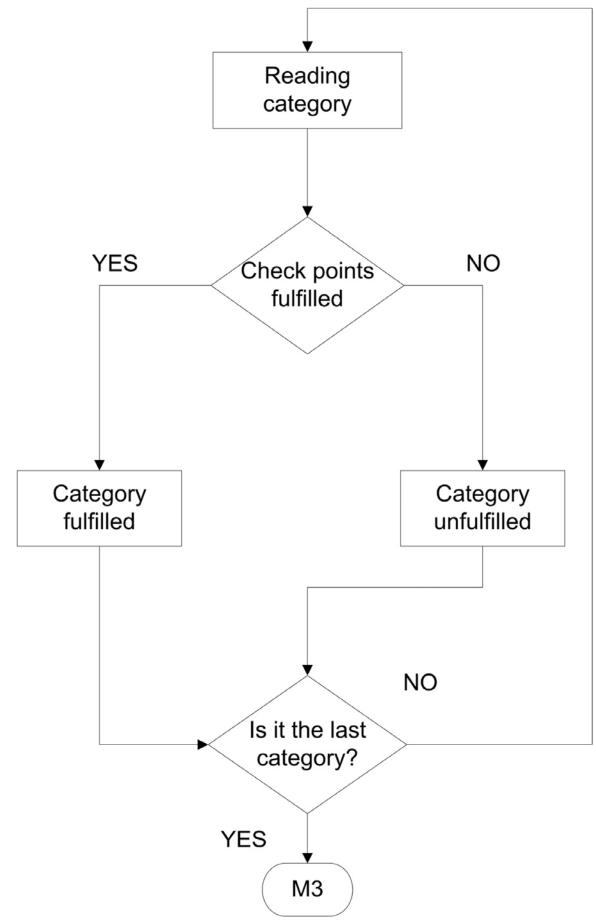


**Fig. 5.** Activities of process M2.

The output of this process is evaluation of student's knowledge, including a complex evaluation of the need to study individual categories. This information is used in the following steps.

### 4.4. Process M2

The set of learning objectives of the given course, i.e. required knowledge of $\text{Category}_i$, $\text{Category}_j$, ..., $\text{Category}_n$, is reduced only to those that are relevant to the student (based on data from M1b). assessing the relevancy of individual categories/learning objectives is done based on meeting or failing the conditions for the given learning objective, i.e. achieving the required knowledge (expressed by the value of variable V5 or by the achieved percentage of score from the check tests during the study). At the end of the learning process (i.e. the end of a semester for example), these relevant objectives, if fulfilled by the student, will complete the set of already identified objectives as fulfilled and thus they will create a complete set of all fulfilled learning objectives. The visualization of process is obvious in Fig. 5.

The process consists of the following steps:

1. Reading the category.
2. Finding out if the check points have been met:
a. V5 value – finding out this value in the initial creation of the study variant and deciding if this value is met (value V5 is lower or equal to V5max) or not (value V5 is higher than V5max)
b. Progress test – each category ends with one progress test. If the student passes this test, this check point is met, otherwise not.
c. Cumulative test – it concerns a summative test after studying *n* categories. This test verifies knowledge of *n* categories in a mixed way. If the student passes this test, this check point is met, otherwise not.
3. If all check points of the category are met, the category is marked fulfilled, otherwise unfulfilled.
4. The last step finds out if the read category was the last one. If yes, process M3 follows. If not, steps 1–3 are repeated with another category.

The output of this process is assessment which categories are fulfilled and which not, based on which the categories are open, or closed respectively, in the student's study variant.

### 4.5. Process M3

Activities of this process lead to the creation of student's personalised study plan itself. When creating it, the input data is processed in several follow-up steps. The whole process is influenced by factors that have impact on the final form of the generated study plan, see Fig. 6:

1. When generating the first pass of the study variant, only study materials whose VARK attribute is ≥20% out of the total ratio are selected.

$$V_{\%} \geq 20,\ A_{\%} \geq 20,\ R_{\%} \geq 20,\ K_{\%} \geq 20$$

In case it concerns the second pass, the process skips step 1.
2. Decision if a set *non-fulfilled* $N = \{\mathrm{Category}_i, \mathrm{Category}_j, \ldots, \mathrm{Category}_n\}$ exists or not.
In case such a set exists, for each $\mathrm{Category}_i$, $\mathrm{Category}_j$, …, $\mathrm{Category}_n$, are read: study materials $SM_i$ ($\mathrm{Category}_i$), $SM_j$ ($\mathrm{Category}_i$), …, $SM_n$ ($\mathrm{Category}_i$), fixed study objects $SO_i$ ($\mathrm{Category}_i$), $SO_j$ ($\mathrm{Category}_i$), …, $SO_n$ ($\mathrm{Category}_i$), $CT_i$ ($\mathrm{Category}_i$), incl. their time ($TSM_{i(CATi)}$, $TSM_{j(CATj)}$, …, $TSM_{n(CATn)}$ + $TSO_{CATi}$, $TSO_{CATj}$, …, $TSO_{CATn}$ + $TCT_i$, $TCT_j$, …, $TCT_n$).
In case such a set does not exist, only $CT_i$ (Subject) are read, incl. their time $TCT_i$, $TCT_j$, …, $TCT_n$).
3. All times of each parts of the study variant are counted resulting in the total time required (TTR):

$$\mathrm{TTR} = \left(\mathrm{TSM}_{i(CATi)},\ \mathrm{TSM}_{j(CATj)}, \ldots, \mathrm{TSM}_{n(CATn)}\right) + \left(\mathrm{TSO}_{CATi},\ \mathrm{TSO}_{CATj}, \ldots, \mathrm{TSO}_{CATn}\right) + \left(\mathrm{TCT}_i,\ \mathrm{TCT}_j, \ldots, \mathrm{TCT}_n\right).$$

4. The value of TTR is compared with the TST value in order to find out if the study variant meets time requirements, i.e. is TTR ≤ TST?
a. Yes: the study variant is approved as student's study plan.
b. No: the study variant is not approved and step 5 follows.
5. The students provides the possibility of devoting more time to the study variant, thus no reduction of the study materials is required, e.g. in case the TTR is only slightly exceeding TCT.
The student decides to provide more time to study the subject:
a. Yes: the study variant is approved as student's study plan.
b. No: the study variant is not approved and steps 6–15 follow. This is the moment of initialisation of generating a reduced study variant.
6. Each study material $SM_i$ ($\mathrm{Category}_i$), $SM_j$ ($\mathrm{Category}_j$), …, $SM_n$ ($\mathrm{Category}_n$) with V5 > 0.7 is set with ISM = 100 (the highest possible importance). This ensures that these SM will not be reduced from the study variant as they are very important for the student to study, see Table 1.
7. Values for individual $V_{\%}$, $A_{\%}$, $R_{\%}$, $K_{\%}$ are sorted in descending order, see Table 1.
8. Each SM at row 1 is set to ISM = 100, see Table 1.
9. Each SM in row 2–4 is calculated for ISM according to the algorithm, see below.

**ISM is calculated:**

$$\mathrm{ISM}_{CATi} = \mathrm{K}_{\%} * \mathrm{V5}\ \text{Example}: \mathrm{DSM}_{CAT5} = 25 * 0.4 = 10$$

$$\mathrm{ISM}_{CATi} = \mathrm{R}_{\%} * \mathrm{V5}\ \text{Example}: \mathrm{DSM}_{CAT5} = 20 * 0.4 = 8$$

10. The last SM is removed from the ISM list and its time (TSM) is subtracted from TTR.
11. Once the ISM of all study materials are calculated, the ISM are sorted in descending importance value.
12. After each reduction of the last SM from the list, the TTR is compared with TST:
a. Yes: the study variant is approved as student's study plan.
b. No: the decision-making process continues.
13. Decision if there is another SM < 100 in the ISM:
a. Yes: return to step 12.
b. No: the decision-making process continues.
14. The last decision-making process in the whole sequence requires an external interference. At this point it is obvious that the reduced study variant exceeds the total study time. The student is asked to provide more time for the study of this variant. Student's decision:
a. Yes: the study variant is approved as student's study plan.
b. No: end – there is no study variant that a student is able to study in the given time period.
15. There is an approved study variant that becomes a student's personalised study plan.

The output of this process is the set of all relevant information and materials for further study.

The algorithm of process M3 is depicted in a flow chart, see Fig. 6.

### 4.6. Learning process

Once the study variant is approved as a student's personalised study plan, the student enters the learning process. The student proceeds in individuals steps where each step represents one category (unit) included in the study plan. The student enters the e-learning process directly into an open category or into a Cumulative test. If the student meets the check test requirements, i.e. achieves the minimum percentage, they can proceed to the next step. If the student fails the test, the category must be studied once again. The student has three attempts to pass the check test (either Progress test or Cumulative test).

If the student fails the check test for the third time, the adaptive systems suggests a change in the study plan. Based on the information about unused study materials, the systems tries to generate a new study variant.

If there are unused study materials, the whole process return to process M2 for generation of a new study variant with the unused study materials.

There are not unused study materials, there is a need of personal interference of the tutor who should consider the whole situation, consult it with the student and find out the reasons of student's failure. The system is only a tool but cannot fully substitute

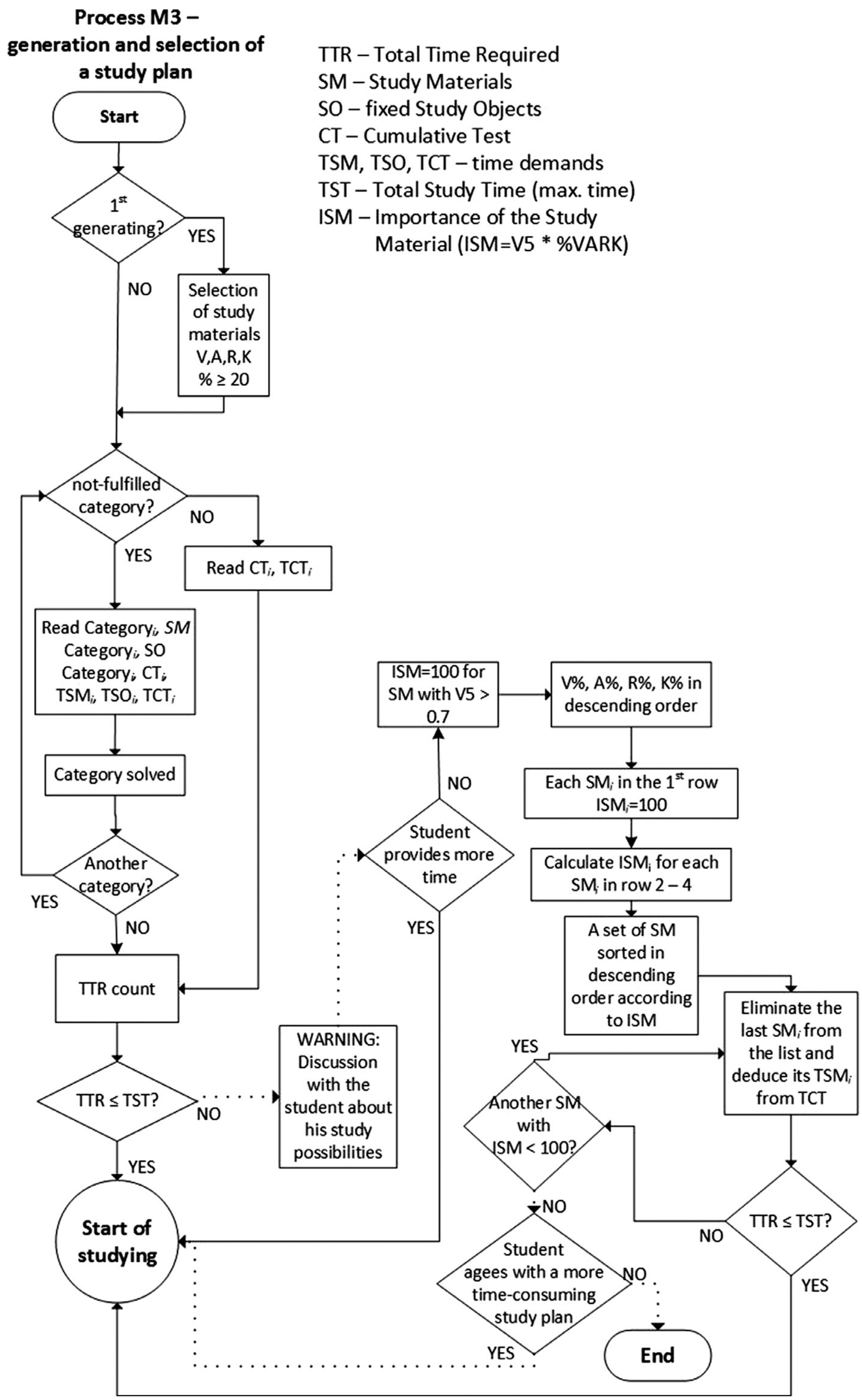


**Fig. 6.** Activities of process M3.

**Table 1**
Example of values for the creation of a reduced study variant.

| CAT. | 5 | 8 | 9 | 11 | 13 | 1 | 2 |
|---|---|---|---|---|---|---|---|
| Value V5 | **0.4** | **0.42** | **0.55** | **0.65** | **0.72** | **0.8** | **0.83** |
| 1. V40% | ISM = 100 | ISM = 100 | ISM = 100 | ISM = 100 | ISM = 100 | ISM = 100 | ISM = 100 |
| 2. K25% | ISM = 10 | ISM = 10.5 | ISM = 13,75 | ISM = 16.25 | ISM = 100 | ISM = 100 | ISM = 100 |
| 3. R20% | ISM = 8 | ISM = 8.4 | ISM = 11 | ISM = 13 | ISM = 100 | ISM = 100 | ISM = 100 |
| 4.A15% | – | – | – | – | – | – | – |

Notes: 1. -„fixed“ study materials., 2, 3. - VARK value with no study materials (percentage $\leq$20%)., 4. - areas of reducing the study materials.

the tutor – this must always be kept in mind. When the tutor has solved this situation, the whole process returns to M2 with certain manual changes.

## 5. Practical verification and results

It can be claimed that our proposed model of an adaptive e-learning system is generally usable for personalisation and adaptation of the educational process of any language course, i.e. in the area which was experimentally verified. However, it does not disqualify it in other areas which have not been not verified yet. The proposed model features a high probability of usage in any course regardless the studied area. In computer science, for instance, examples can be the following (they contain large number of content-rich units, which suit best to our proposed model):

- Operating systems,
- Computer networks,
- Software engineering,
- Relational databases.

In order to apply and implement the model, it is necessary to meet these conditions:

- Division of the course into units (categories),
- Creation of a didactic test with questions corresponding to categories, recording the time for student's answers,
- Creation of materials in individual units and their categorisation as V, A, R, or K,
- Potential modification of IF-THEN rules of the knowledge base of the expert system.

However, to claim its general usability, further research must be carried out.

Our proposed adaptive e-learning system has been practically verified on two groups of students who participated in the course KIP/ANGI3 at the Department of Informatics and Computers, University of Ostrava. The first tested group took the course in the winter semester 2014/2015, the second group in the winter semester 2015/2016. Both groups counted 16 students.

The objective of the verification was to test students' knowledge of the English language using the VARK questionnaire and a didactic test. The knowledge was assessed by the expert system based on several input criteria with subsequent determination of the need of further study of the tested categories. All areas contain materials of various types (V, A, R, K), which are then displayed to each student according to their sensory preferences and the total study time assigned to study course ANGI3. This results in displaying only the preferred materials and the system eliminates materials that are not relevant, e.g. due to their time requirements, student's sufficient knowledge, etc.

The practical verification was carried out using two web applications. The first application, LMS Test, consists of the following steps:

1. Student's login into the system
2. Loading of the VARK questionnaire and its completion
3. Loading of the didactic test and its completion
4. Assessment of the didactic test using the expert system with subsequent assessment of the need of further study of each category

The scheme of the LMS Test application is depicted in Fig. 7:

A part of LMS Test is the expert system with IF-THEN rules:

The input linguistic variables to the system are as follows:

- V1 – number of correct answers within a category
- V2 – weight of correct answers within a category
- V3 – importance of the category for further study

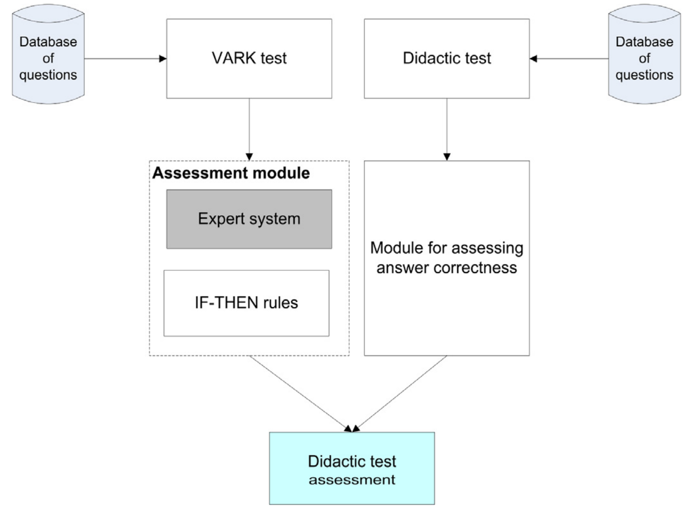


**Fig. 7.** Scheme of an LMS test.

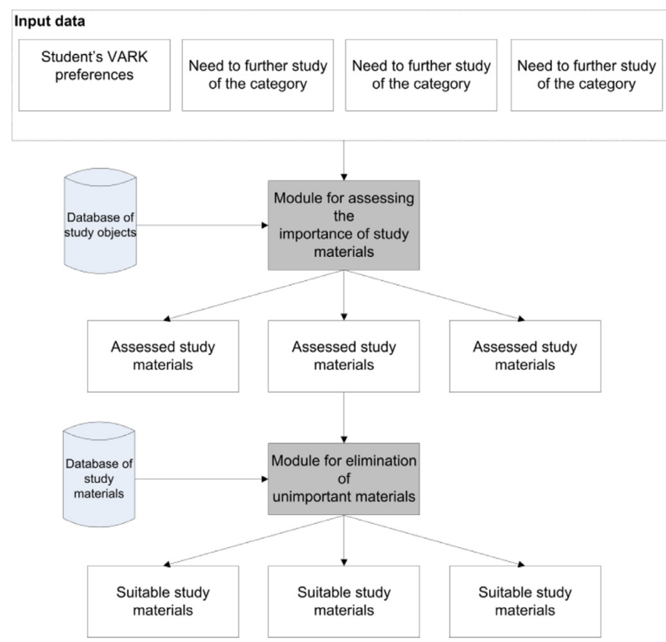


**Fig. 8.** Scheme of LMS Adaptive e-learning.

- V4 – time spent on answers within a category

The output linguistic variable from the system is as follows:

- V5 – need of further study of a category

The second application, LMS Adaptive e-learning, consists of the following steps:

1. Student's login into the system
2. Loading of the VARK preferences and the need of further study of all categories
3. Assessment of very important materials
4. Assessment of all other materials
5. Elimination of irrelevant materials
6. Displaying of relevant materials to the student

The scheme of the LMS Adaptive e-learning application is depicted in Fig. 8:

All categories of the didactic test are separately assessed by the expert system and the results are visualised to the student, see below an example of one of the results: (Table 2)

**Table 2**
Results of didactic test.

| Parameter<br>Past continuous | Value |
|---|---|
| Correct answers (in %) | 50% |
| Weight of correct answers | 5 |
| Importance for further studies | 10 |
| Time spent on answering with respect to standard time (in %) | 57.5% |
| Necessity of further studies | **big** |
| **Present perfect continuous** | |
| Correct answers (in %) | 100% |
| Weight of correct answers | 5.75 |
| Importance for further studies | 7 |
| Time spent on answering with respect to standard time (in %) | 63.75% |
| Necessity of further studies | **medium** |
| **Past perfect** | |
| Correct answers (in %) | 100% |
| Weight of correct answers | 6.33 |
| Importance for further studies | 5 |
| Time spent on answering with respect to standard time (in %) | 88.33% |
| Necessity of further studies | **more or less medium** |
| **Prepositions** | |
| Correct answers (in %) | 83.33% |
| Weight of correct answers | 5 |
| Importance for further studies | 3 |
| Time spent on answering with respect to standard time (in %) | 42.5% |
| Necessity of further studies | **very low** |

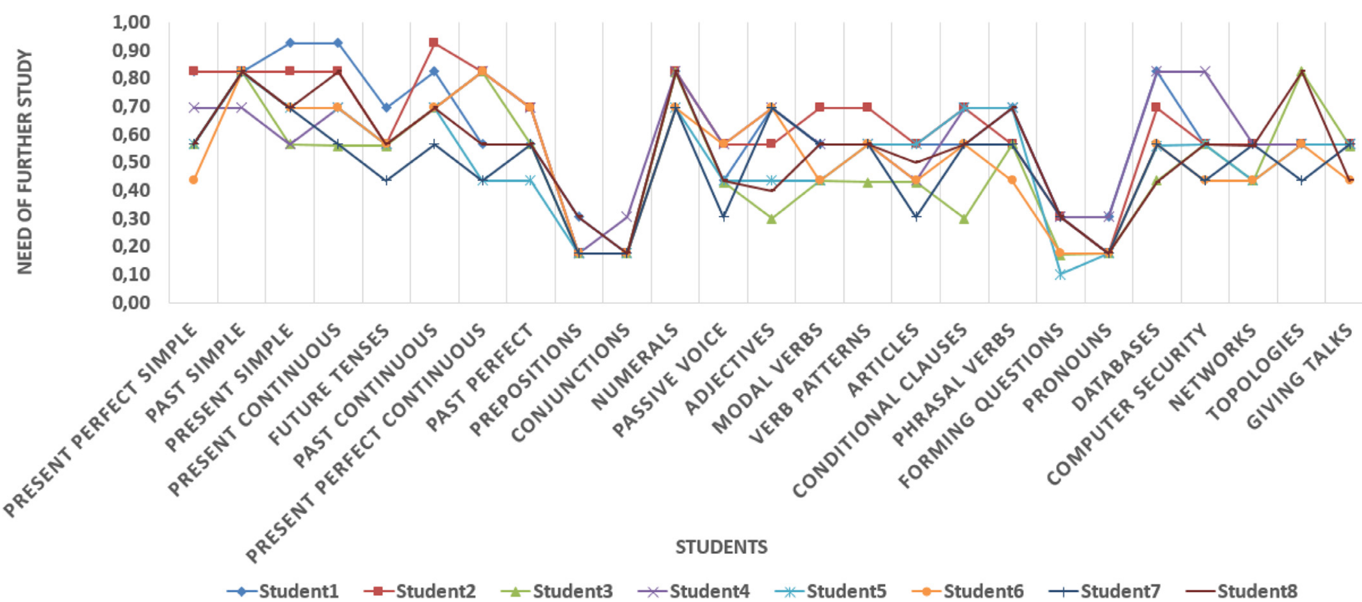


**Fig. 9.** Evaluation of studentś results – graph 1.

Below is depicted statistical evaluation of students' results and the need of further study of given categories for selected students. The first graph depicts results of a group of eight students tested in the winter semester 2014/2015. The graph reveals that certain categories are very easy for the students, thus the need to study them s very low: Prepositions, Conjunctions, Forming question a Pronouns. Other categories are much different, though: e.g. Past simple, Numerals (Fig. 9).

The second graph depicts the same results of a group of eight students tested in the winter semester 2015/2016. It can be stated that students have difficulties in very similar categories (Fig. 10).

In order to assess the second part, we have selected 12 student from the first assessment. This assessment consisted in loading relevant/suitable materials for the students based on their VARK preferences, results of their studies and available time for their studies.

The threshold value set as the maximum time of their studies (total study time) was 2350 min (i.e. TST = 2350).

Next, the total count of materials of individual categories representing the VARK preferences was also uploaded. Each material belongs to one VARK category. Individual categories have the following count of materials:

- V – 39 materials
- A – 40 materials
- R – 35 materials
- K - 32 materials

Next, results of given students were loaded after the time trimming, i.e. after assessment of important and less important materials. Then the system assessed how many materials from given category will be shown to the student. Individual students were divided groups according to their VARK preferences. The following graphs show the students in groups V, A, R, K preferences. The results reveal that materials from the given preference are eliminated the least, unlike those with the lowest ISM, i.e. the least important.

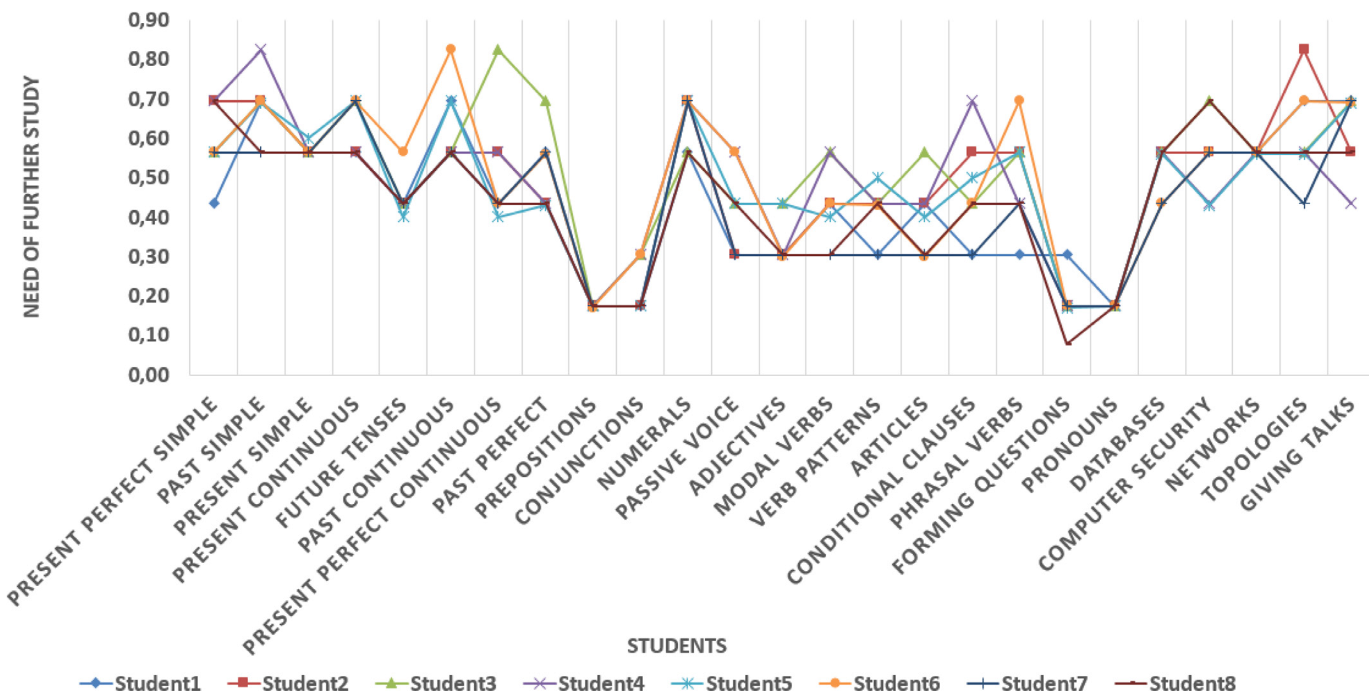


**Fig. 10.** Evaluation of studentś results – graph 2.

**Table 3**
VARK results for the first group of students with the highest V preference.

| | V | A | R | K |
|---|---|---|---|---|
| **Student 1** | **40.91** | 22.73 | 13.64 | 22.73 |
| **Student 2** | **33.33** | 16.67 | 30 | 20 |
| **Student 3** | **31.03** | 27.59 | 13.79 | 27.59 |
| **Student 4** | **34.62** | 19.23 | 19.23 | 26.92 |

In addition, the results depend on the need of further study (V5) of the given category and the total time required (TTR) for the study.

**Results of students with the highest V preference**

The following table presents the VARK results for the first group of students with the highest V preference. The table reveals that each student has a different percentage ratio of V preference with respect to other preferences (Table 3).

Next table depicts the total time of the materials calculated for individual students based on their need of further study (V5) in all categories. It is different for each student. In addition, the table provides information on the total time after the time trimming. Columns Number of V, A, R, K show the number of materials of individual preference. It is obvious that all students have most of V-materials, but preferences with higher ration have much considerable trimming of materials. For example, for student 1 and 3, it is R-materials, for student 2 A-preference (Table 4, Fig. 11).

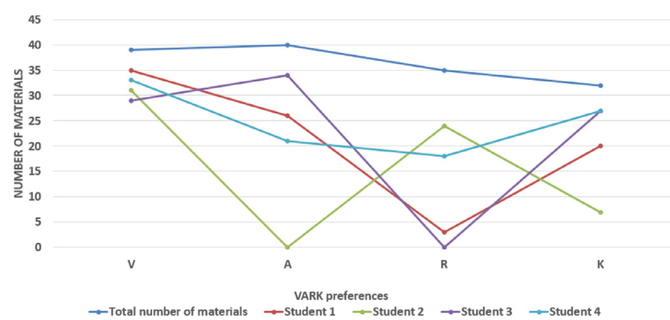


**Fig. 11.** Development of the number of materials for individual students.

**Results of students with the highest A preference**

The following table presents the VARK results for a group of 4 students with the highest A preference (Table 5).

Next table shows again the times before and after trimming as well as the number of materials for individual VARK preferences. It is again clear that the trimming for A preference is the smallest or none. For example, for student 1 the trimming for V-materials is the highest as his V-preference is the lowest (Table 6, Fig. 12).

### 5.1. Assessment of the questionnaire

The experimental verification also included a questionnaire survey among the students who took part in a pilot course in order to verify the benefits and functionality of the proposed model.

**Table 4**
Total time of the materials calculated for individual students.

| | Total time of materials for study before trimming | Total time of materials for study after trimming | Number of V-materials | Number of A-materials | Number of R-materials | Number of K-materials |
|---|---|---|---|---|---|---|
| **Student 1** | 2679 | 2288 | 35 | 26 | 3 | 20 |
| **Student 2** | 3095 | 2258 | 31 | 0 | 24 | 7 |
| **Student 3** | 2679 | 2292 | 29 | 34 | 0 | 27 |
| **Student 4** | 3122 | 2294 | 33 | 21 | 18 | 27 |

**Table 5**
VARK results for the second group of students with the highest V preference.

| | V | A | R | K |
|---|---|---|---|---|
| **Student 1** | 10 | **35** | 25 | 30 |
| **Student 2** | 12.9 | **38.71** | 25.81 | 22.58 |
| **Student 3** | 17.86 | **35.71** | 32.14 | 14.29 |
| **Student 4** | 20 | **26.67** | 26.67 | 26.67 |
| **Student 5** | 25 | **34.38** | 28.13 | 12.5 |
| **Student 6** | 25.64 | **33.33** | 20.51 | 20.51 |
| **Student 7** | 19.35 | **38.71** | 22.58 | 19.35 |
| **Student 8** | 24.14 | **27.59** | 20.69 | 27.59 |

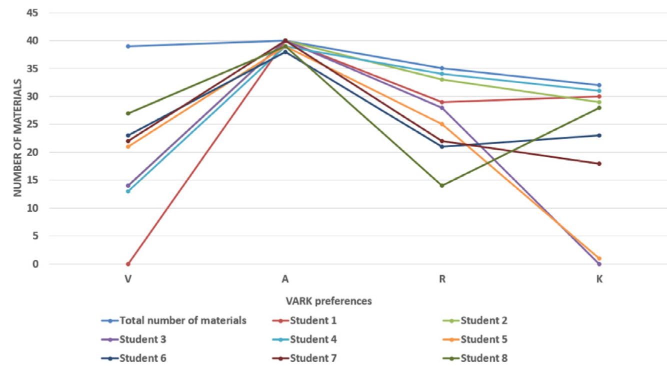


**Fig. 12.** Development of the number of materials for individual students.

The following section shows the questions asked to and answers from 11 students who took part in the pilot course verification.

Question 1: How do you perceive the possibility of assessing each grammar category/topic separately? (compared with only the total score).

- Answer 1: beneficial
- Answer 2: I don't care
- Answer 3: not beneficial

Question 2: What amount of study material did the e-course contain?

- Answer 1: low
- Answer 2: adequate
- Answer 3: high

Question 3: The format of the offered materials (.pdf, .ppt, .mp3 or .avi) was suitable.

- Answer 1: yes
- Answer 2: no

Question 4: Do you consider beneficial that the piloted course included materials from the preceding e-courses?

- Answer 1: yes
- Answer 2: no

Question 5: Compared with the preceding e-course, the studies were.

- Answer 1: much longer
- Answer 2: longer
- Answer 3: the same
- Answer 4: shorter
- Answer 5: much shorter

Question 6: The conditioned progress through the course was convenient.

- Answer 1: yes
- Answer 2: no
- Answer 3: partially

Question 7: Was it beneficial to revise the content of the preceding e-courses in the case that was recommended by the system?

- Answer 1: yes
- Answer 2: no

Question 8: Compared with the preceding e-courses, the style of the e-course "made" me study.

- Answer 1: more
- Answer 2: the same
- Answer 3: less

Question 9: Do you think that if your knowledge of English corresponded with input requirements for ANGI3, the time of your studies would be longer/ the same/shorter than in a regular e-course?

- Answer 1: longer
- Answer 2: the same
- Answer 3: shorter

Results of the questionnaire in a graphical form, see Fig. 13:

The results show that the students accepted the proposed model very positively. There is one comments to the results – in Question 1, there were only 10 answers as 1 student did not mark any of the answers, thus there are 10 instead of 11 answers.

## 6. Discussion

Our proposed adaptive model for an educational process consists of the following steps, described in detail in chapter 4:

- Acquisition of information about student – students' data on areas concerned in the decision-making.
- M1a - acquisition of information about student's sensory preferences and their evaluation.

**Table 6**
Total time of the materials calculated for individual students.

| | Total time of materials for study before trimming | Total time of materials for study after trimming | Number of V-materials | Number of A-materials | Number of R-materials | Number of K-materials |
|---|---|---|---|---|---|---|
| **Student 1** | 2424 | 2290 | 0 | 40 | 29 | 30 |
| **Student 2** | 2424 | 2299 | 14 | 40 | 33 | 29 |
| **Student 3** | 3122 | 2292 | 14 | 40 | 28 | 0 |
| **Student 4** | 3122 | 2281 | 13 | 39 | 34 | 31 |
| **Student 5** | 3122 | 2283 | 21 | 39 | 25 | 1 |
| **Student 6** | 3122 | 2292 | 23 | 38 | 21 | 23 |
| **Student 7** | 3122 | 2286 | 22 | 40 | 22 | 18 |
| **Student 8** | 3122 | 2281 | 27 | 39 | 14 | 28 |

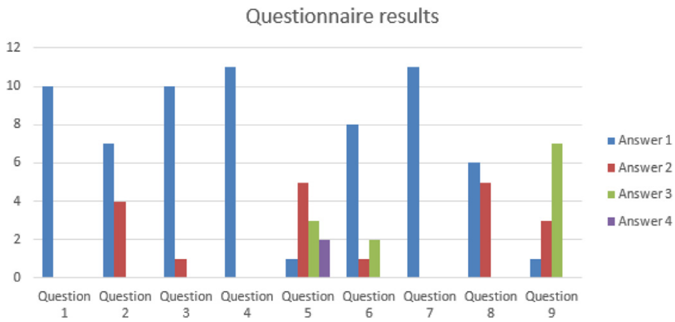


**Fig. 13.** Questionnaire results.

- M1b - acquisition of information about student's level of knowledge and its evaluation.
- M2 – defining the objectives for the student based on the analysed information.
- M3 – process of finding a study variant for the given student. All the data on the student, course, course categories, test, and study materials are read.

In process M1a, the questionnaire of sensory preferences is read and evaluated. The output for each student are values of V,A,R,K preference and their percentage ratio.

In process M1b, the didactic test is read. Each question contains several possible answers. Each question is assigned to a particular category. The test is completed and assessed by an expert system. The output of this process is evaluation of student's knowledge, including a complex evaluation of the need to study individual categories.

In process M2, course categories are read and they are assessed either as fulfilled or unfulfilled by the student. Based on that, they will be either closed or open to the student.

In process M3, suitability of study materials is assessed based on outputs from processes M1 and M2. Then, a proposed algorithm is applied in order to create a (reduced) study variant. The output from process M3 are relevant information and study materials for further studies.

The above-presented results and practical verification, described in detail in chapter 5, reveal several findings that will be described below.

**The assessment of the need of further study and finding problematic categories for further study in the practical verification**

The results presented in Figs. 8 and 9 show that students usually achieve low score (high need of study) for the following categories of the didactic test:

- Past Simple
- Present Continuous
- Numerals

This trend is significant both for students in the winter semester 2014/2015 and students in winter semester 2015/2016. The above-mentioned categories are problematic for students and thus it is necessary to pay higher attention to them and to monitor students' progress when dealing with such categories.

In addition, the results show that students usually achieve high score (low need of study) for the following categories of the didactic test:

- Prepositions
- Conjunctions
- Forming questions
- Pronouns

**Table 7**
Studentś results.

| Category | Need of further study |
|---|---|
| Present perfect simple | 0.825 |
| Past simple | 0.825 |
| Present simple | 0.825 |
| Present continuous | 0.825 |
| Future tenses | 0.57 |
| Past continuous | 0.92666 |
| Present perfect continuous | 0.825 |
| Past perfect | 0.70 |
| Prepositions | 0.18 |
| Conjunctions | 0.18 |
| Numerals | 0.825 |
| Passive voice | 0.565 |
| Adjectives | 0.565 |
| Modal verbs | 0.695 |
| Verb patterns | 0.695 |
| Articles | 0.565 |
| Conditional clauses | 0.695 |
| Phrasal verbs | 0.565 |
| Forming questions | 0.305 |
| Pronouns | 0.175 |
| Databases | 0.695 |
| Computer security | 0.565 |
| Networks | 0.565 |
| Topologies | 0.565 |
| Giving talks | 0.565 |

This trend is significant, again, for both tested groups (2014/2015 and 2015/2016).

**Usage of the assessment of the need of further study of a given student and their future development**

It is also highly beneficial to assess the need of further study of a given student and their future development. As an illustration, the results of Student 2 from the winter semester 2014/2015 are used. The following table presents student's results: (Table 7)

The results imply that student's further development primarily requires to focus on Present perfect simple, Past simple, Present simple, Present continuous, Past continuous, Present perfect continuous, Numerals.

On the contrary, the student achieved good results in Prepositions, Conjunctions, Forming questions a Pronouns. all of these categories were assessed as „very low" or "low" need of further study.

During future study of the student, there will be a need to test the student again for the worst categories and to monitor student's progress.

**Implementation of the way of selecting important study materials according to VARK preferences and trimming unimportant materials**

A detailed algorithm of calculating the importance of a study material and the algorithm of trimming unimportant study materials is closely described in Chapter 4, Table 1.

The main idea of this process results from the need of labelling which materials are more or less important for a given student. The level of importance depend on two aspects – student's VARK preferences (i.e. the preferred type of materials) and which category the material belongs to (i.e. which category from the didactic test the material is assigned to). The higher the need of further study of a given category, the higher the importance of the material.

Trimming of unimportant materials (i.e. of low importance) is necessary mainly with respect to TST (Total Study Time), primarily due to the fact that TST is often lower than the total count of times of materials necessary for student's further study. In other words, TST requires elimination of certain materials, i.e. less important, in order that the total count of remaining materials for the student would be equal or less than TST.

Considering this fact, it is highly important to set the TST correctly taking into consideration the database of available materials. There is also a need to consider a hypothetical situation when a student achieves more than one highest VARK preference (percentage equality). In such a case, the student would be asked, for example, to complete another VARK test to be able to select a suitable VARK preference.

## 7. Conclusion

The paper presented a proposal of a new approach to adaptive e-learning systems. The approach is based on several methods and it is divided into several processes. First, the authors focused on the division of the studied subject into categories which are assigned with different importance. Then, an initial didactic test was created where the questions were related with the categories from the previous step. The initial didactic test is assessed by an expert system based on input values from the didactic test (V1 – number of correct answers within a category, V2 – weight of correct answers within a category, V3 – importance of the category for further study, V4 – time spent on answers within a category). The output from the expert system is assessment of the need to study a given category (V5). The initial information provided by the student also contains VARK preferences from the questionnaire of sensory preferences. Its output is a percentage ratio of individual preferences used for providing the best suitable materials for the study.

Based on the above-described results, suitable materials are selected for each category. Each material is assessed using an algorithm which calculates its importance (ISM). For each student, the study variant is then adapted based on the length of study times TST and TCT. Thus, a reduced study variant, if applicable, is created containing only the most suitable study materials based on VARK preferences and the need to study a given category.

Our future research should focus on other adaptive features of an e-learning system, among others:

- Assessment of progress test during studies in e-learning with subsequent adaptation based on their results.
- Displaying suitable materials for acquisition of necessary knowledge in parts of the tests that were seriously failed (i.e. displaying those parts of an e-learning course that are crucial for the student to proceed to next parts of the course).

## Acknowledgment

This work was supported by the project "LQ1602 IT4Innovations excellence in science" and during the completion of a Student Grant SGS02/UVAFM/2016 with student participation, supported by the Czech Ministry of Education, Youth and Sports.

## Appendix

Acronyms

| | |
|---|---|
| ANGI3 | English for specialisation degree 3 |
| AT | Auto -test |
| CT | Cumulative test |
| ES | Expert system |
| ISM | Importance of study material |
| ITS | Intelligent tutoring system |
| LMS | Learning management system |
| PrT | Progress test |
| SM | Study material |
| SO | Study object |
| SV | Study variant |
| TCT | Time of cumulative test |
| TSM | Time of study material |
| TSO | Time of study object |
| TST | Total study time |
| TTR | Total time required |
| V1-V5 | Variable1 – Variable5 |
| VARK | Visual, Aural, Read/Write, Kinaesthetic |

## References

Andrews, R., & Haythornthwaite, C. (Eds.). (2007). *The Sage handbook of e-learning research*. Sage.

Bos, E., & van de Plassche, J. A. (1994). Knowledge-based, english verb-form tutor. *Journal of Artificial Intelligence in Education, 5*(1), 107–129.

Bradac, V. (2013). Adaptive model to support decision-making in language learning. In *Proceedings of EDULEARN2013* (pp. 4036–4045). Barcelona.

Bradac, V. (2014). Enhacing assessment of students' knowledge using fuzzy logic in e-learning. In *Proceedings of 10th international scientific conference on distance learning in applied informatics DIVAI 2014* (pp. 251–262).

Bradac, V., Walek, B., Klimes, C., & Farana, R. (2014). A new way how to assess student's knowledge of the English language in e-learning. In *Proceedings of ICERI2014: 7th international conference of education, research and innovation* (pp. 1708–1717).

Brusilovski, P. (1996). Methods and techniques of adaptive hypermedia. *User Modeling and User Adapted Interaction, 6*(2-3), 87–129.

Brusilovski, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. *The Adaptive Web*, 3–53. https://scholar.google.com/citations?view_op=view_citation&hl=cs&user=s6RpNfAAAAAJ&citation_for_view=s6RpNfAAAAAJ:IjCSPb-OGe4C.

El Alami, M. (2011). New methods for student learning assessment. In *4th International conference of education, research and innovation (ICERI)* (pp. 1231–1238). Madrid.

El-Hmoudova, D., Milkova, E., & Garant, G. (2012). Computer-based testing in the field of foreign language assessment. In *Proceedings of efficiency and responsibility in education*. Prague: Czech University of life sciences.

Etienne, W. (1987). Artificial intelligence and tutoring systems. *Computational and cognitive approaches to the communication of knowledge*. Los Altos, San Francisco, CA: Morgan Kauffmann.

Ferster, B. (2014). *Teaching machines: Learning from the intersection of education and technology* p. 216. John Hopkins University Press.

Jurickova, R. (2012). Optimizing the teaching of a foreign language in regards to student learning styles and e-learning. In *Proceedings of 9th international conference on efficiency and responsibility in education* (pp. 203–2012).

Kakoty, S. (2012). Fuzzy expert logic to evaluate learner's expertise level in e-learning environment. In *Proceedings of 2012 IEEE international conference on advanced communication control and computing technologies* (pp. 148–152). Ramanathapuram.

Klasnja-Milicevic, A., Vesin, B., Ivanovic, M., Budimac, Z., & Jain, L. C. (2016). *E-learning systems: Intelligent techniques for personalization (vol. 112)*. Springer.

Klimes, C. (2011). Model of adaptation under indeterminacy. *Kybernetika, 47*(3), 356–369.

Kostolanyova, K. (2012). *Teorie adaptivního e-learningu*. Ostrava: University of Ostrava.

Li, J. W., Chang, Y. C., Chu, C. P., & Tsai, C. C. (2012). A self-adjusting e-course generation process for personalized learning. *Expert Systems with Applications, 39*(3), 3223–3232.

Liao, S. H. (2005). Expert system methodologies and applications—a decade review from 1995 to 2004. *Expert Systems with Applications, 28*(1), 93–103.

Lin, C. H., Warschauer, M., & Blake, R. (2016). Language learning through social networks: Perceptions and reality. *Language Learning & Technology, 20*(1), 124–147.

Murphy, M., & McTear, M. (1997). Learner modelling for intelligent CALL. In *Proceedings of the sixth international conference on user modeling* (pp. 301–312). Vienna Springer.

Nedbalova, S., & Kostolanyova, K. (2015). individualization of foreign language teching through adaptive eLearning. In *International conference on web-based learning (ICWL)* (pp. 159–170). GuangzhouChin: LNCS. ISBN: 978-3-319-32865-2.

Novak, V., Perfilieva, I., & Dvorak, A. (2016). Insight into fuzzy modeling.

Novak, V., & Lehmke, S. (2006). Logical structure of fuzzy IF-THEN rules. *Fuzzy Sets and Systems, 157*(15), 2003–2029.

Pokorny, M. (2012). *Expertní systémy* p. 190. Ostrava: University of Ostrava.

Rudak, L. (2012). Susceptibility to e-teaching. In *Proceedings of ICT for competitiveness* (pp. 10–16). Karviná.

Sánchez-Torrubia, M. G., Torres-Blanc, C., & Trivino, G. (2012). An approach to automatic learning assessment based on the computational theory of perceptions. *Expert Systems with Applications, 39*(15), 12177–12191.

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior, 55*, 1185–1193.

Tzouveli, P., Mylonas, P., & Kollias, S. (2008). An intelligent e-learning system based on learner profiling and learning resources adaptation. *Computers & Education, 51*(1), 224–238.

Verdú, E., Verdú, M. J., Regueras, L. M., de Castro, J. P., & García, R. (2012). A genetic fuzzy expert system for automatic question classification in a competitive learning environment. *Expert Systems with Applications, 39*(8), 7471–7478.

Virvou, M. (2001). Web passive voice tutor: An intelligent computer assisted language learning system over the WWW. In *Proceedings of IEEE international conference on advanced learning technologies* (pp. 131–134). Madison.

Woolf, B. P. (2010). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann.

Yildiz, O. (2013). Improved fuzzy modelling to predict the academic performance of distance education students. *International review of research in open distance learning*. Athabasca: Athabasca University Press.

Walek, B., & Bradac, V. (2015). Expert system for evaluating tests in e¬learning system. *Global Journal on Technology, 8*, 119–124.

Wang, Y. H. (2014). Proposing an E-learning system for personalised EFL vocabulary learning. In International symposium on computer, consumer and control (IS3C)*IEEE, Taichung, Taiwan* (pp. 1152–1155). ISBN: 978-1-4799-5277-9.

Zadeh, L. A. (1988). Fuzzy logic. *Computer, 21*(4), 83–93.

Zadeh, L. A. (1983). The role of fuzzy logic in the management of uncertainty in expert systems. *Fuzzy Sets and Systems, 11*(1-3), 199–227.