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Intelligent Tutoring Systems

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Abstract: The importance of intelligent tutoring systems has rapidly increased in past decades. There has been an exponential growth in the number of ends users that can be addressed as well as in technological development of the environments, which makes it more sophisticated and easily implementable. In the introduction, the paper offers a brief overview of intelligent tutoring systems. It then focuses on two types that have been designed for education of students in the tertiary sector. The systems use elements of adaptivity in order to accommodate as many users as possible. They serve both as a support of presence lessons and, primarily, as the main educational environment for students in the distance form of studies – e-learning. The systems are described from the point of view of their functionalities and typical features that show their differences. The authors conclude with an attempt to choose the best features of each system, which would lead to creation of an even more sophisticated intelligent tutoring system for e-learning.

Keywords: Adaptive systems, e-learning, ITS, intelligent tutoring systems.

1 Introduction

Computer-based learning is very favoured among the users of e-learning, mainly if it concerns languages [2], and as described in Ref. [14], languages can be taught and learnt through e-learning, although with limited possibilities and results. Thus, various systems have been developed in order to overcome this insufficiency.

If any discussion about e-learning, adaptive learning, and similar issues is to be discussed, recognised researches in this field should also be mentioned in order to define our approach. The most suitable starting point is undoubtedly Brusilovski's work concerning adaptive hypermedia and educational systems [6], and primarily Ref. [8]. His approach is the basis for other researchers that deal with intelligent tutoring systems (ITSs). An example of an ITS is presented by Virvou [18], who developed *Passive Voice Tutor*, which is a system for teaching the passive voice to Greek students. This ITS, in fact, includes knowledge of one domain, tools for modelling a student, recommendation generator to a student, and user interface. In Ref. [19], another ITS system was created; this one aimed at the system of English tenses – *English Tutor*. *English Tutor*, similarly to *Passive Tutor*, is usable only for a limited spectrum of language – grammar tenses. Moreover, it was overcome by *Passive Voice Tutor* in its ability to identify not only mistakes in tenses, but also spelling and other mistakes likely to occur in the answer as well. *Passive Voice Tutor* also creates a long-term profile of the student, which is not possible in *English Tutor*.

Comparing the above-mentioned systems, all of them differ from the two systems described. Either they do not work with learning styles and focus only on a limited spectrum of a subject matter, see Refs. [18, 19], or they do not use fuzzy-oriented expert systems [10] for adaptation of the system, see Ref. [16]. Thus, a comprehensive, universally adaptive system that would combine elements necessary for modern e-learning, such as integrating learning styles/sensory preferences, identification of student's knowledge, assigning suitable

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learning objects, and creating a personalised study plan, which has been tested and run in practice, cannot be found in current sources.

The following section introduces two systems that were designed to eliminate/remove the above-mentioned limitations. The reasons for their choice are that both of them were designed at a university for tertiary education (i.e. the same target group); both were designed for e-learning; both integrate adaptive features but in a different way, which predetermines them to be very prospective when combined; and, last but not least, both can be used independent of the subject taught.

2 Adaptive Learning

The learning environment is considered adaptive if it is able to monitor and interpret users' activities, deduce users' needs and preferences based on the interpreted activities, and finally dynamically adjust the learning process [7, 15].

Adaptation can be of various forms, which can be divided into the following categories:

1. Adaptation of user environment,
2. Adaptation of learning content,
3. Adaptation of search, and
4. Creation of learning content and adaptive support of cooperation.

The first category, adaptation of user environment, adapts, e.g. colour scheme of the learning environment, used fonts and sizes, structure, and sequence of user-performed actions. The second category, adaptation of learning content, aims at making the learning process as much natural to the user as possible, resulting in optimisation from both the quality and time points of view. This adaptation includes, e.g. a dynamic change of the structure of the learning content, navigational elements in learning materials, and a dynamic selection of parts of learning materials. The third category takes basis in gathered information about a student to offer him such materials that are the most beneficial for the student at the given moment. The last category focuses on communication between users and on other ways of group activities. This adaptation lies in facilitating the process of communication and cooperation and ensuring a good combination of users within a group [9].

3 Virtual Teacher

There are numerous ways on how to try to make learning more effective using new technologies. New technologies are represented by a computer in our case. A teacher can use the computer more than just to passively transfer electronic study materials to students. A teacher can, to a certain limit, pass over his knowledge to a computer, his active way of teaching, and his reactions to certain situations or problems. Moreover, a computer can, to a certain limit, repeat a teacher's behaviour. This results in an imperfect computer copy of a teacher – a virtual teacher. Compared to a real teacher, a virtual teacher has its limits as well as several key advantages:

- It can be at more places at the same time, i.e. it can serve more students scattered throughout the world. Their number is limited only by hardware means.
- It can gather experience from a lot of real teachers. The amount of experience is limited by hardware means.
- It can reliably remember a large number of data about each student's progress. It can then adapt the learning process.
- It can last hundreds of years and improve itself.
- After the initial operation, it has low operational costs compared to real teachers [1].

This idea led to a proposal of a complex system to realise e-learning adaptive education, primarily focused on adaptation of the content as it is the major source of information for a student in an electronic environment and significantly influences the learning process.

3.1 Structure of the System Barborka

The learning management system (LMS) Barborka, as the system was named, works with a deeply structured study material to adapt it with respect to sensory preferences and levels of difficulty. The study is controlled by an algorithm whose parameters are set by an expert on adaptive education [13]. The system activities are divided in modules *Student*, *Author*, and *Expert*, described below.

3.1.1 Module *Author*

The content of this module are individual courses prepared for adaptive learning. Each course is divided into lessons, frames, variants, and layers. The learning content is inserted into the system by an author using forms as formatted text added with metadata. The author creates only the content, but has nothing to do with adaptation. Technically, the author has to be familiar only with basic work in the editor and know the meaning of individual form fields. The author does not have to know HTML or any other language.

3.1.2 Module *Student*

In adaptive learning, this module is primarily responsible for gathering information about a student, i.e. to find out his learning style and to evaluate the learning progress. Currently, the learning style is analyses using a questionnaire [17], whose results are not very accurate, but it can be filled-in in 5–10 min compared to other questionnaires taking 1 h and more. This module follows a student's learning progress, primarily time in individual parts and the level of correct answers. The student is offered those materials that correspond to his characteristics the most. The student can also adapt the displayed study material to his needs. Thus, he can choose another sensory form or another level of knowledge. The system monitors such changes together with the student's other activities.

3.1.3 Module *Expert*

This module defines the activities of the so-called virtual teacher, which displays suitably sequenced layers of the given frame in a suitable variant. The activities of the virtual teacher are set by a set of rules designed by an expert in adaptive learning. Each rule consists of assumptions and inferences. An assumption of the rules is the student's knowledge.

The inference is the depth individual layers should have and the sensory type of the given frame. The inference can also be adapted in the sequence of individual layer types using three methods: by defining the basic sequence, which determines the basic sequence of layer types; by defining the sequence at the beginning and at the end; and by defining the way of displaying of so-called multi-layers, i.e. more layers of the same type. Those are displayed either gradually with all layers of the same type, or individual types of multi-layers alternate according to the multi-layer sequence.

The system uses two algorithms. The following part briefly introduces their principle.

3.2 Algorithm of Adaptive Selection of Learning Style

Based on the rules, this algorithm creates a recommended learning style for a given student (i.e. it specifies sensory variants and defines the sequence and depth of a layer). The algorithm contains abbreviations and their values as follows:

- Sign **Fix** gets values 0, 1 and 2 and determines the rule activity:
  - 0: the rule determines the sequence at the beginning or at the end.
  - 1: the rule determines the basic sequence.
  - 2: the rule determines the layer depth.
- Sign **Int** gets values 0, 1, and 2 and determines the sequence of displayed layers:
  - 0: sequence set by the author.
  - 1: successive multi-layers.
  - 2: alternate multi-layers.
- Variable **MSt** represents the individual characteristics of a student.
- Variable **Form** represents one of sensory types: verbal, visual, aural, and kinaesthetic.
- Variables **Vri**, where **i** is a natural number, represent layer type.
- Variables **Hli**, where **i** is a natural number, represent layer depth.

In Ref. [14], the algorithm is introduced as follows:
Input: *Vector of static characteristics of a real student*
Student ({ver,viz,aud,kin}, MStAfek, MStSoc, MStSyst, {MStExp,MStTeor},
{MStHol,MStDetail}, MStHloub, MStAutoreg, MStVysl).

Output: *Learning style recommended for a given student in a form of a vector*
StylSt (Form, {Vr1, Hl1}, {Vr2, Hl2}, {Vr3, Hl3}, ..., Int).

Algorithm:

1. *Find the most similar virtual student to the current real student.*
2. *Find all rules in the rule list with identical left part of characteristics; if there is no correspondence of any characteristic of the current virtual student with a value in the rules, find a rule with the closest value of this characteristic.*
3. *According to the first rule of type {ver,viz,aud,kin}⇒ Form select a group of variants (depth 1, 2, 3) with an optimal sensory form.*
4. *Perform unification of the right sides of other rules and determine an optimal sequence of layer types of recommended depths.*
   4.1. *Select all rules for which Fix = 1.*
   4.2. *Design an initial sequence of layers, consider value Int.*
   4.3. *Select all rules for which Fix = 0.*
   4.4. *Place layers inferred in the rules before or after the created structure, consider value Int.*
   4.5. *Select all rules for which Fix =2.*
   4.6. *For layer types that do not have set, their depth by preceding rules perform depth determination according to the read rules.*
5. *Define the learning style for the current (virtual) student as a recommended sequence of layers and their variant depths of the recommended form:*
   StylSt (Form, {Vr1, Hl1}, {Vr2, Hl2}, {Vr3, Hl3}, ..., Int).

3.3 Algorithm of Adaptive Control of Learning

Based on the above-selected learning style, this algorithm selects particular layers that are to be displayed. Apart from that, the algorithm controls system reactions to an incorrect answer to a question.

This algorithm uses similar abbreviations and terminology as the previous one.

Input: 1. *Recommended learning style of the student*
StylSt (Form, {Vr1, Hl1}, {Vr2, Hl2}, {Vr3, Hl3}, …, Int).
2. *Selected course, lesson, frame*
3. *Metadata of frames of current lesson of current course*

Output: *Recommended sequence of displaying particular layers of current frame.*

Algorithm:
1. *Read information about the recommended learning style of the student.*
2. *Read information about frame variants.*
3. *Use points 1 and 2 to construct a corresponding sequence of the layers of the frame.*
4. *For all layers of the frame, i = 1, …, n.*
   4.1. *Display the content of the layer i to the student.*
   4.2. *If the current layer is a testing one, then*
      4.2.1. *Record correctness of the student's answers to questions and tasks in the lesson.*
      4.2.2. *If the answer is correct, go to 4.3.*
      4.2.3. *If the answer is incorrect and no reaction defined, display a standard error message.*
      4.2.4. *If the answer is incorrect and the reaction defined, display the reaction.*
      4.2.5. *If the answer is incorrect the first time, enable one more trial to answer it – go to 4.1.*
      4.2.6. *If the answer is incorrect the second time and the value Hli < 3, increase Hli = Hli + 1 for each exposition and testing layers; go to 4.1.*
      4.2.7. *If the answer is incorrect the second time and the value Hlx = 3, display the correct answer.*
   4.3. *i = i + 1.*
   4.4. *End of the cycle for the layers of the frame.*
5. *If the answers are incorrect in the long term, adjust MStVysl = –100 or if the answers are correct in the long term, adjust MStVysl = 100 and use the algorithm of adaptive selection of learning style once again.*

The used expert rules (IF-THEN type) constitute "pedagogical experience, knowledge, and skills" in controlling personalised learning. Of course, it cannot be assumed that the currently defined rules will be optimal for all types of students. Similarly, pedagogues can be of different opinions on their formulation. Thus, the system is designed and implemented in a way that enables to easily refine or replace them without any program change. Every pedagogue-expert can adjust and verify his own theory on controlling adaptive learning.

4 Adaptive eLearning

4.1 Focus

The objective was to create an adaptive e-learning system, primarily for language education.

The pedagogical perspective considered the student itself, i.e. to gather information about his learning and absorbing information (sensory preferences), in order to gather information about his input knowledge of language. Such information is used to adapt the learning process at the beginning as well as during the learning process according to the initial and progress tests. The primary objective in this perspective was to adapt current e-learning courses that are rigid and the same for all students towards individual students' needs.

The technical perspective considered a proposal of a new methodology in language education, which stems from a general model of decision making under indeterminacy [12] when deciding on the next step in the learning process. It means to introduce such processes into current LMSs, which would result in more effective adaptation of the content and form of the content. It is done based on identification of a student's knowledge and its assessment (adaptation of the content) and identification of a student's sensory preferences (adaptation of the form of the content). It leads to the creation of a personalised study plan for a given student. Identification and creation of a personalised study plan are done using a fuzzy oriented expert system containing a knowledge base with IF-THEN linguistic rules. The rules have been created by an expert on language education.

A complex model of an adaptive e-learning system has integrated the above-described areas into several subsequent processes in a way that enables to adapt the whole learning process. Processing information from a student, the teacher and expert leads to a significantly effective and user-friendly way of teaching/learning of language using e-learning.

4.2 Structure of Adaptive eLearning

Adaptive eLearning is the name of an application designed as a new e-learning tool. Figure 1 depicts the scheme of its decision-making processes.

Acquisition of information about a student – acquisition of information in areas concerned with the decision-making process.

M1a – process of completion of information about a student's sensory preferences. A detailed study was presented in the work in Ref. [3].

M1b – process of completion of information about a student's knowledge and its assessment. A detailed study was presented in works in Refs. [4, 5].

M2 – process of creating a set of admissible solutions, i.e. formulating objectives of language learning based on the description of the given situation and formulating admissible solutions.

M3 – modelling the progress of individual proposed solutions – each admissible solution is assigned a set of situations and their time sequence that arises from the given solution; such modelling is cycled until the first solution is found. This solution is approved as the study plan for the given student.

4.3 Definition of Individual Parts

4.3.1 Acquisition of Information about a Student

Input information is information gathered before the learning process itself as well as during its progress. The input is a didactic test and a questionnaire of sensory preferences. Selection of the didactic test depends on the course that the student has selected in the given semester. Selection of the didactic test implies values

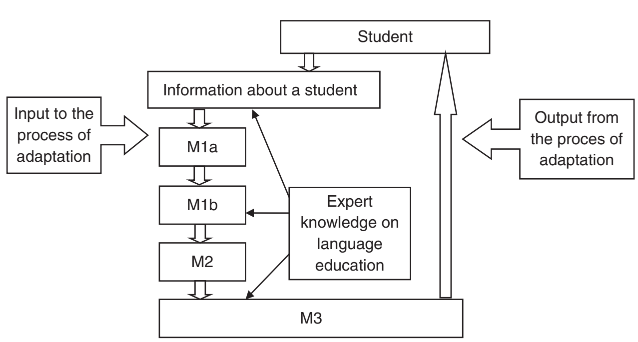

Figure 1: Scheme of the Decision-Making Process.

related to the given course and test. The questionnaire of sensory preferences is only one and standardised. It does not relate to any particular course or to other values.

4.3.2 Process M1a

Process M1a determines the combination of sensory preferences based on percentage calculation of frequency:

$$\mathrm{V}_{\%} = [\mathrm{Frequency}V/(\mathrm{Frequency}V + \mathrm{Frequency}A + \mathrm{Frequency}R + \mathrm{Frequency}K)] * 100.$$
$$\mathrm{A}_{\%} = [\mathrm{Frequency}A/(\mathrm{Frequency}V + \mathrm{Frequency}A + \mathrm{Frequency}R + \mathrm{Frequency}K)] * 100.$$
$$\mathrm{R}_{\%} = [\mathrm{Frequency}R/(\mathrm{Frequency}V + \mathrm{Frequency}A + \mathrm{Frequency}R + \mathrm{Frequency}K)] * 100.$$
$$\mathrm{K}_{\%} = [\mathrm{Frequency}K/(\mathrm{Frequency}V + \mathrm{Frequency}A + \mathrm{Frequency}R + \mathrm{Frequency}K)] * 100.$$

4.3.3 Process M1b

Process M1b is a process that assesses the level of knowledge of the given student in the given course. The didactic testis assessed as a whole:

$$(Q_i + Q_j + \ldots + Q_n) \geq Q_{\mathrm{TOTAL}} * 0.4.$$

If the minimum requirements are met, step 2 follows. In the opposite case, the student is alerted about not meeting the minimum knowledge and is forwarded to enrol in a lower-level course.

This phase of assessment of the didactic test consists in assessment of each category separately. The process uses a fuzzy logic expert system [11] and a knowledge base containing a set of created IF-THEN rules to process the input variables (*V1–V4*) and assess the output variable (*V5*). A sample rule is provided:

IF *V1* is SMALL **AND** *V2* is SMALL **AND** *V3* is VERY BIG **AND** *V4* is BIG **THEN** *V5* is EXTREMELY BIG.

The knowledge base contains 135 linguistic rules.

4.3.4 Process M2

This process consists in selecting only relevant study objectives ($\mathrm{Category}_i$, $\mathrm{Category}_j$, …, $\mathrm{Category}_n$) for the given student out of the set of all study objectives. This is done based on the assessed objective relevance from M1b. Relevance assessment means meeting or failing to meet the requirements for the given objective, i.e. acquiring the needed knowledge (expressed by *V5* value, or by progress and cumulative test results). At the end of the learning process, the selected relevant objectives, if successfully met, are added to already completed study objectives and thus create a whole set of study objectives.

4.3.5 Process M3

Activities in this process lead to creation of a personalised study plan itself. When creating a plan, the input data are processed in several follow-up steps. The whole process is affected by factors influencing the final form of the generated study plan.

The first pass of generating consists in selecting relevant study materials (SMs) whose VARK attribute is ≥ 20% out of the total count ($\mathrm{V}_{\%} \geq 20$, $\mathrm{A}_{\%} \geq 20$, $\mathrm{R}_{\%} \geq 20$, $\mathrm{K}_{\%} \geq 20$). In case it is not the first pass, the following procedure is carried out (see Figure 2).

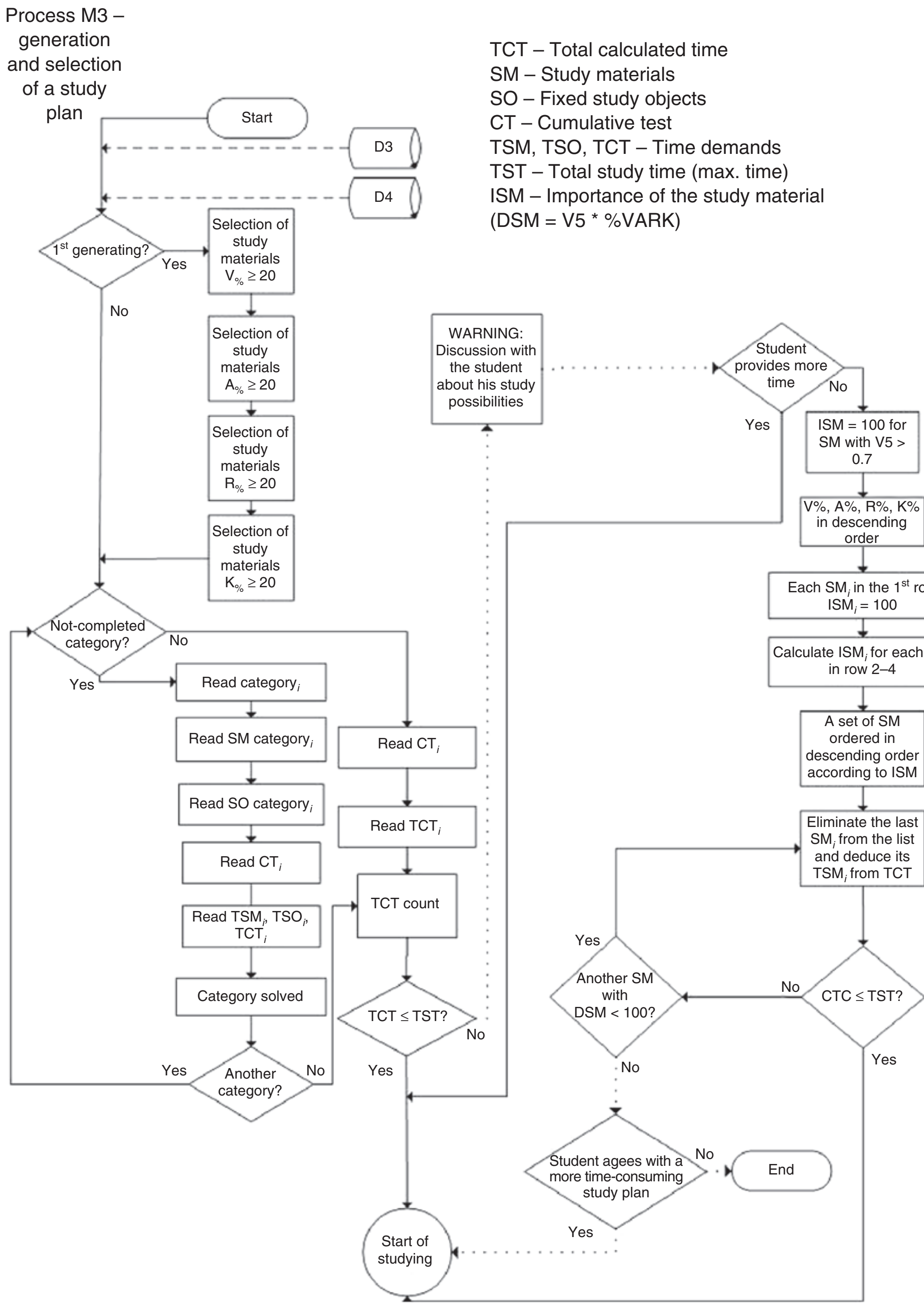

Figure 2: Flowchart of the Whole M3 Process of Generating a Study Plan.

Assessment of the importance of a study material is performed as follows:

Each study material SM_i (Category$_i$), SM_j (Category$_j$), …, SM_n (Category$_n$) with an attribute $V5 > 0.7$ is set to importance ISM = 100. This ensures that these SMs would be eliminated as it is highly important to study those categories (see Table 1).

Values for individual $V_{\%}$, $A_{\%}$, $R_{\%}$, $K_{\%}$ are sequenced in descending order (see Table 1).

Table 1: Sample Values to Create a Reduced Study Plan.

CAT.	5	8	9	11	13	1	2
V5	0.4	0.42	0.55	0.65	0.72	0.8	0.83
1. $V_{40\%}$	ISM = 100	ISM = 100	ISM = 100	ISM = 100	ISM = 100	ISM = 100	ISM = 100
2. $K_{25\%}$	ISM = 10	ISM = 10.5	ISM = 13.75	ISM = 16.25	ISM = 100	ISM = 100	ISM = 100
3. $R_{20\%}$	ISM = 8	ISM = 8.4	ISM = 11	ISM = 13	ISM = 100	ISM = 100	ISM = 100
4. $A_{15\%}$	–	–	–	–	–	–	–

0.4 – value V5. ISM = 100 – "fixed" study materials. $A_{15\%}$ – VARK value that has no selected study materials. $K_{25\%}$ – areas to eliminate study materials.

Each SM in row 1 is set to ISM = 100 (see Table 1).
Each SM in rows 2–4 is set to ISM according to the algorithm (see Table 1).
ISM is calculated as follows:

$$\mathrm{ISM}_{\mathrm{CATi}} = \mathrm{K}_{\%} * V5 \quad \text{Example: } \mathrm{ISM}_{\mathrm{CAT5}} = 25 * 0.4 = 10.$$
$$\mathrm{ISM}_{\mathrm{CATi}} = \mathrm{R}_{\%} * V5 \quad \text{Example: } \mathrm{ISM}_{\mathrm{CAT5}} = 20 * 0.4 = 8.$$

4.4 Study

Once the study plan for a given student has been approved, the student can start the learning process. The student proceeds through individual steps, when each step represents a category (lesson) added in his study plan. The student enters the learning process either into an open category or into a cumulative test. If the student passes the test, i.e. reaches the minimum requirements, he can proceed to another step. If the student fails the test, he returns to studying the category and has two more re-takes. If the student fails in all of the three attempts, the adaptive system suggests a change in the study plan. Based on the information about unused study materials, it decides if it is possible to generate a changed study plan. If there are unused study materials, the process goes back to M2 to generate a new study plan.

If there are no unused study materials, it is the pedagogue who must interfere to re-assess the study results, and decides on appropriate actions to take. Having re-assessed the whole situation, the process goes back to M2 again.

5 Merging the Systems

A comparison of the two above-mentioned systems can be done only partially. It is obvious that the systems differ right in the core of their structure and in the principle of using adaptive elements.

A different and more interesting view than a mere comparison is the view how to merge both systems into one – into a system that would take over the best of Virtual Teacher and Adaptive eLearning. It means such features that make them specific against other ITSs as well as those that make them adaptive. Individual features are described according to the processes used/done by the systems:

1. Testing and assessing sensory preferences – used by both systems. Adaptive eLearning without manual interference.
2. Testing and assessing level of knowledge – assessment by an expert system (Adaptive eLearning).
3. Creating a study plan – various depths of study materials (Virtual Teacher); no predefined students' models (Adaptive eLearning, each student has a unique study plan); works with time (Adaptive eLearning).

4. Possibility to adjust the form of study materials – Virtual Teacher.
5. Diagnostics of a student's progress – used by both systems but assessed by different algorithms.
6. System versatility – yes for Virtual Teacher; Adaptive eLearning was verified on language learning and shows signs of versatility.

Adaptive eLearning is a modular system, i.e. a part (module) can be added or taken out (or used in another system). Adaptive eLearning has its strength in the area of assessment of a student's knowledge by an expert system, which, used by the Virtual Teacher, would lead to more accurate selection of the lesson, layer, and depth of study materials. Integrating the time perspective of studying into the Virtual Teacher would also significantly bring the Virtual Teacher closer to optimisation of the learning.

6 Final Structure of the Proposed System

The structure of the system that is being proposed should contain all elements from Section 5, primarily for the following reasons:
1. It is highly necessary to work with the student's sensory preferences in order to assure an individual study plan. Moreover, automated assessment brings relief to the teacher and makes it more effective.
2. Assessment of a student's knowledge by an expert system (combined with step 1) provides a very good base for creating a study plan tailored to the given student.
3. The study plan itself needs to have more paths (levels or difficulties) in order to assure the possibility for the student to fluctuate between the paths when needed (to slow down or speed up).
4. This is enabled by the assessment of the student's sensory preferences in step 1.
5. This is needed in order to evaluate the student's performance, which makes it possible to adapt it during the studies.
6. The proposed system not only has to address one subject, but also, if possible, to be used across the board; it would make it a very universal but efficient tool for e-learning.

All the above-mentioned points will be a subject of future research, testing, and evaluation in order to specify and state whether the authors selected the most suitable and usable modules of the proposed system. The research will aim at the system's simplicity, usability, user friendliness, and hardware requirements, as well as at whether the system provides the desired results, i.e. student's improved performance during their studies.

7 Conclusion

This paper presented two representatives of existing ITSs – Virtual Teacher and Adaptive eLearning. These systems use adaptive elements in order to be usable for as wide target group as possible. Although the systems are different in their structure of processes taking place in them and in the methodology of using study materials, a deeper analysis reveals that keeping the identical elements and implementing the differences (with certain limitations) can lead to newer, more sophisticated ITSs. This finding lays bases for future research of the authors.

Bibliography

[1] I. Beaumont, User modelling in the interactive anatomy tutoring system ANATOM-TUTOR, in: *User Models and User Adapted Interaction*, pp. 21–45, Springer, Netherlands, 1994, Available from: http://wwwis.win.tue.nl/ah94/Beaumont.html, Accessed 15 May, 2015.
[2] E. Bos and J. van de Plassche, A knowledge-based, English verb-form tutor, *J. Artif. Intell. Educ*. **5** (1994), 107–129.

[3] V. Bradáč, Adaptive model to support decision-making in language e-learning, in: *International Conference on Education and New Learning Technologies – Proceedings*, 5th ed., Barcelona, pp. 4036–4045, 2013, ISBN: 978-84-616-3822-2.
[4] V. Bradáč, Enhancing assessment of students' knowledge using fuzzy logic in E-learning, in: *10th International Scientific Conference on Distance Learning in Applied Informatics*, pp. 251–262, Wolters Kluwer, Štůrovo, 2014.
[5] V. Bradáč and C. Klimeš, Language E-learning based on adaptive decision-making system, in: *Proceedings of the 12th European Conference on e-Learning*, pp. 48–58, Reading, ACPI, 2013, ISBN 978-1-909507-84-5.
[6] P. Brusilovsky, Methods and techniques of adaptive hypermedia, *User Model. User Adapt. Interact.* **6** (1996), 87–129.
[7] P. Brusilovsky, Adaptive navigation support, in: P. Brusilovsky, A. Kobsa and W. Neidl, eds., *The Adaptive Web: Methods and Strategies of Web Personalization, Lecture Notes in Computer Science*, vol. 4321, pp. 263–290, Springer-Verlag, Berlin, 2007.
[8] P. Brusilovsky and E. Millán, User models for adaptive hypermedia and adaptive educational systems, in: *The Adaptive Web*, *LNCS*, vol. 4321, pp. 3–53, Springer-Verlag, Berlin, 2007, ISBN 978-3-540-72078-2.
[9] P. De Bra, Aha! design [online], 2003, Available from: http://aha.win.tue.nl:18080/aha/Get/ahadesign/?concept=ahadesign.adaptivepresentation, Accessed 20 April, 2015.
[10] D. Fum, O. Giagrandi and C. Tasso, The use of explanation-based learning for modeling student behavior in foreign language tutoring, in: *Intelligent Tutoring Systems for Foreign Language Learning*, vol. 80, pp. 151–170, Verlag, Berlin, 1992, ISBN: 978-3-642-77204-7.
[11] H. Habiballa, V. Novák, A. Dvořák and V. Pavliska, *Using software package LFLC 2000*, in: *2nd International Conference Aplimat 2003*, Bratislava, pp. 355–358, 2003.
[12] C. Klimeš, Model of adaptation under indeterminacy, *Kybernetika* **47** (2011), 355–368.
[13] K. Kostolányová, J. Šarmanová and O. Takács, Learning, in*: Proceedings of the 9th European Conference on e-Learning*, pp. 107–107, Academic Publishing Limited, Porto, 2010, ISBN 978-1-906638-83-2.
[14] M. Murphy and M. McTear, Learner modelling for intelligent CALL, in: *Proceedings of the Sixth International Conference on User Modeling*, pp. 301–312, Springer, Vienna, 1997.
[15] A. Paramythis and S. Loidl-Reisinger, Adaptive learning environments and e-Learning standards, In: *ECEL, Linz: Academic Conferences and Publishing International*, pp. 181–194, Sonning Common, England, 2003.
[16] M. Pokorný, *Expertní Systémy*, Ediční středisko CIT OU, University of Ostrava, Ostrava, 2004.
[17] O. Takács, K. Kostolányová and J. Šarmanová, Experimental verification of learning styles in e-Learning, in: *Efficiency and Responsibility in Education 2011*, pp. 302–311, Czech University of Life Sciences Prague, Prague, 2011.
[18] M. Virvou, Web Passive Voice Tutor: an intelligent computer assisted language learning system over the WWW, in: *IEEE International Conference on Advanced Learning Technologies*, pp. 131–134, Madison, WI, 2001, ISBN: 0-7695-1013-2.
[19] E. Wenger, *Artificial Intelligence and Tutoring Systems*, MorganKaufmann Publ., Los Altos, CA, 1978.