A framework for creating automated online adaptive tests using multiple-criteria decision analysis

Konstantina Chrysafiadi
Department of Informatics
University of Piraeus
Piraeus, Greece
kchrysafiadi@unipi.gr

Christos Troussas
Department of Informatics
University of Piraeus
Piraeus, Greece
ctrouss@unipi.gr

Maria Virvou
Department of Informatics
University of Piraeus
Piraeus, Greece
mvirvou@unipi.gr

***Abstract*— Towards the last decade, digital education has become a burning issue in the related scientific literature and involves the production of Intelligent Tutoring Systems (ITSs). ITSs are adaptive educational applications that enrich the tutoring and learning processes with "intelligence" by divulging the abilities and weaknesses of each student, in order to provide him/her with a personalized learning experience. A crucial factor of adaptive learning systems is testing, and indeed adaptive testing. It is a challenge to create an adaptive test that includes the most suitable exercise/question/activity of a large pool of test items for a particular learner taking into consideration her/ his particular learning characteristics, needs and ability. In this paper, a framework for creating automated adaptive tests using multiple-criteria decision analysis and the weighted sum model is presented. The presented framework takes into consideration multiple students' criteria along with the types of exercises and the desirable learning objective. The aforementioned assessment framework was incorporated in two adaptive e-learning systems and was fully evaluated. The evaluation results are very encouraging.**

Keywords—e-learning, adaptive testing, multiple-criteria decision analysis, weighted sum model

I. INTRODUCTION

Intelligent adaptive learning systems are quickly emerging due to the growing need of applying intelligence and personalization in digital learning. The intended design of these data-adaptive solutions seeks to enable distinct learning at an individualized level of tutoring. Adaptive learning systems are designed to dynamically adjust to the level or type of course content based on personalized student's abilities, needs or skill attainment, in ways that accelerate a learner's performance with both automated procedure and instructors' interventions [1]. The intent of these systems is to use proficiency and determine what a student really knows and to accurately and logically move students through a sequential learning path to prescribed learning outcomes and skill mastery. In view of the above, adaptive systems have the potential to shift education for the sake of students by providing a student-centric design.

A crucial factor of adaptive learning systems is testing. In particular, adaptive tutoring systems use automated processes of student assessment approaches to self-assessment, diagnostic and formative assessment. The more adaptive to the learners' needs and abilities the tests are, the more effective and accurate they are. The digital area and the adaptive learning systems facilitate the process of creating adaptive tests, reducing the time and effort that are required to create such tests.

In literature review, adaptive tests, which are created automatically by a computer system or application, are called Computer Adaptive Tetst (CAT) [2]. Computer-adaptive tests are designed to adjust their level of difficulty—based on the responses provided—to match the knowledge and ability of a student. Considered to be on the leading edge of assessment technology, computer-adaptive tests represent an attempt to measure the abilities of individual students more precisely, while avoiding some of the issues often associated with the traditional nature of standardized tests. For students, computer-adaptive testing offers a shorter testing session with a smaller number of questions, since only those questions considered appropriate for the student are offered. On the other hand, assessment creators have to create a larger pool of test items so that testing systems have enough questions to match the varied abilities of all students taking the exam. The most current forms of computer-adaptive testing are typically administered online, and because the scoring is computerized, teachers and students can get test results more quickly than with paper-and-pencil tests.

To built an algorithm that choose the most suitable exercise/question/activity of a large pool of test items for a particular learner is a difficult process that requires the identification and audit of many criteria that concern the learner's abilities and needs. Such criteria are: knowledge level, related prior knowledge or experience, learning preferences and learning styles, learning objectives e.t.c. Therefore, the use of multiple-criteria decision analysis (MCDA) [3] seems to be ideal for making decisions about which test items are best suited to the learning needs and abilities of an individual learner. MCDA explicitly evaluates multiple conflicting criteria in decision making. There is a variety of approaches and methods for MCDA [4]. In the presented method of creating an adaptive test, the weighted sum model (WSM) is used. The reason for this choice is that WSM is the best known and simplest MCDA method for evaluating a number of alternatives in terms of a number of decision criteria [5]. WSM uses weight multiple benefit criteria and calculates the importance of each alternative. In Fig.1 the presented system's architecture is presented.

The remainder of this paper is organized as follows. In Section 2, the related work in adaptive testing and MCDA is

2577-1655/18/$31.00 ©2018 IEEE
DOI 10.1109/SMC.2018.00049

presented. In Section 3, the criteria that are taking into consideration for the creation of an adaptive test are described. In Section 4, the algorithm that has been developed for creating adaptive tests using WSM is presented. In Section 5, the presented method's evaluation is described. Finally, in Section 6, the conclusions drawn from this work and the future work are presented.

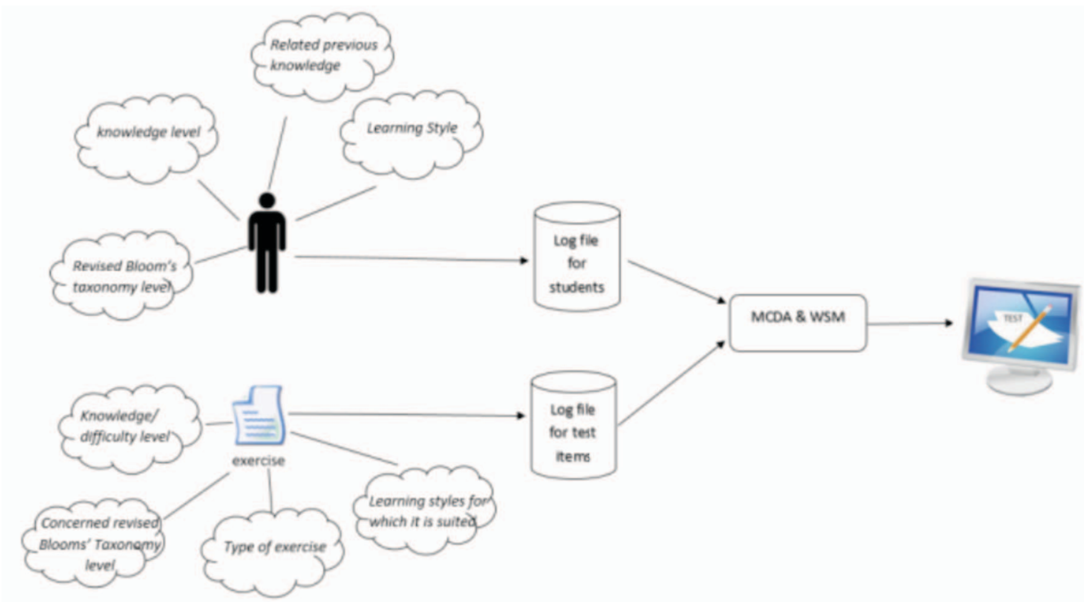

Figure 1: The system's architecture

II. Related work

The computerized adaptive testing is a crucial factor in adaptive e-learning systems since it promotes personalized learning; the related scientific literature has slightly dealt with it though. Many e-learning systems have used computer adaptive testing for learners's practice and/or assessment [6-8]. In [9], the authors introduced a new item selection algorithm that integrates experts' knowledge modeled by fuzzy linguistic information that enhances the adaptation of testing to student's competence level. In [3], the authors proposed a framework for evaluating, comparing, and improving the effectiveness of competence indicators in the various publications for teaching materials in primary school based on different viewpoints. Their aim was to select the aspired intelligent assessment systems for teaching materials. In [4], the authors proposed an analytical approach for the primary school selection problem using the analytic network process and fuzzy cognitive maps. In [10], the authors have described conceptual and technical foundations for using computerized adaptive testing to assess modelers' skills for an operationalization of more rigorous assessment of modeling skills. In [2], the authors presented a method to provide adaptive tests and useful feedback to the examinee, which would be used in a platform for certification of digital competencies for every French citizen. In [11], the authors proposed an architecture for enabling computerized adaptive testing with arbitrarily complex item types, putting a particular focus on integration in online learning settings. This architecture is designed in a way that enables technology-proficient users to integrate adaptive testing in their online learning platform. Furthermore, in [12] the development and implementation of an adaptive testing system for supporting several assessment functions and different devices is presented. In [13] a method for adaptive selection of test questions according to the individual needs of students within a web-based educational system is presented. The particular method, however, neither concerns specialised learner's characteristics like learning style nor combines different learner's characteristics that imply the learner's ability and needs in a more representative way. Also, it does not use multiple-criteria decision analysis. However, after a thorough investigation in the related scientific literature, we came up with the result that there was no implementation of a framework for adaptive assessments taking into consideration multiple students' criteria along with the types of exercises and the desirable learning objective using multiple-criteria decision analysis and the weighted sum model.

III. Description of criteria

The presented framework for creating adaptive tests takes into consideration multiple students' criteria along with the types of exercises and the desirable learning objective. The criteria are presented below:

a) Learner's knowledge level in the knowledge domain: The main criteria of an adaptive learning system in order to decide about the learning material (instruction, practice, assessment) that is suitable for her/ him to be delivered, is her/ his knowledge level in the teaching knowledge domain. An educational system that creates adaptive tests has to identify the learner's knowledge level and adapt the test dynamically to each individual learner's needs.

b) Related previous knowledge of the learner: The previous knowledge that the learner may has and which is related to the learning material affects either the learner's knowledge level or exercises' difficulty level, which will have to be involved in the adaptive personalized test. For example, if a learner, who is being teaching a computer programming language, has previous experience on computer programming and programming languages, then s/he has to be provided with a test that includes more complex programming exercises than simple exercises that concern variables' declaration or statements' structure [14]. Another example is the learning of a foreign language that is affected, usually, by the learner's previous knowledge of another foreign language. So, the English learning process for a learner can be affected by her/ his previous knowledge in French or German [15, 16].

c) Learner's learning style: Individuals differ in how they learn. Each individual has her/ his own 'style' of learning. There are many theories that classify people according to the way they learn. A simple categorization of learning styles is the VAK model [17, 18]. According to the VAK Learning Styles Model, an individual learns better by using one (or two) of the following three ways:

- Visual: a learner, who has visual learning style, prefers the visual means of teaching and retains information better when it is presented in, for example, pictures, diagrams and charts. Therefore, exercises of the adaptive test, which will be provided to the particular learner, should include visualized material, like graphs, images, diagrams etc.
- Auditory: a learner, who has auditory learning style, prefers listening to what is being presented. S/ he participated in discussions and likes to read aloud the learning material, hearing her/his own voice. Therefore, exercises of the adaptive test, which will be provided to the particular learner, should have transcribed pronunciation, as well as they should give the learner the ability to record her/ his voice while reading the exercise. A good idea is the display of an agent that gives/ reads the exercise.
- Kinesthetic: a learner, who has kinesthetic learning style, prefers a physical experience. She likes a "hands-on" approach and responds well to being able to touch or feel an object. S/he is good at experiments and likes to listen music while reading. Therefore, the adaptive test can be accompanied with music. Furthermore, exercises like crosswords or problem solving with direct visualization of the results seem to be more ideal for those type of learners. However, all the exercises of an online test are suitable for kinesthetic learners as they used keyboard, mouse, tablet to solve them.

The learning style of a learner may not always be the same for some tasks. The learner may prefer one learning style for one task, and a combination of others for a different task. An adaptive educational environment or application has to be able to identify each time the preferred learning style for each individual.

d) Type of exercises: There are many types of exercises that can be included into a test. Some types are: right/ wrong, multiple choice, crosswords, fill in the gap, matching exercise etc.. In many circumstances the type of an exercise is related to the exercise's difficulty, to the learner's learning style or to the learning outcome that is aimed to be succeeded. For example, usually right/wrong exercises are chosen to evaluate the learner's understanding of the learning material at the early stages of the learning process, while crosswords and fill in the gaps exercises are preferred to be used for assessing more complex issues. The type (or types) of exercises that are included into a test are chosen by the instructor.

e) The desirable learning objective according to the revised Bloom's taxonomy: The taxonomy of educational objectives is a framework for classifying statements of what we expect or intend students to learn as a result of instruction. It can be used as a means of facilitating the construction of banks of learning items that measure the same educational objective [19, 20]. Therefore, a such taxonomy can facilitate the creation of adaptive tests. The most known taxonomy is the revised Bloom's taxonomy. According to this, thinking skills are organized into the following six levels, from the most basic to the more complex levels of thinking:

- Level 1 – Remember: recall facts and basic concepts.
- Level 2 – Understand: explain ideas or concepts.
- Level 3 – Apply: use information in new situations.
- Level 4 – Analyze: draw connections among ideas.
- Level 5 – Evaluate: justify a stand or decision.
- Level 6 – Create: produce new or original work.

TABLE I. EXAMPLES OF EXERCISES ACCORDING TO THE REVISED BLOOM'S TAXONOMY

Revised Bloom Taxonomy Level	Examples of exercises /activities
Remember	Memorizing things; listing things; defining; recognizing facts or procedures
Understand	Identifying, describing and/ or classifying; recognizing an option, a fact, a method, a procedure, a situation etc; explaining facts, things, procedures etc; select the right answer, method, procedure etc
Apply	Executing procedures; implementing methodologies and/or theories; solving problems; demonstrating a method
Analyze	Comparing methodologies or solutions; relating information, facts; examining the solutions of a problem; organizing
Evaluate	Giving benefits/mistakes; selecting the most appropriate method or theory to use; udging an action or a problem solution
Create	Planning strategies; designing ways for solving problems; constructing a method; generating new ideas

Therefore, according to the learning objective, which implies the knowledge level, the experience and the ability of the learner, the educational system can create adaptive tests that include from very simple right/ wrong questions (at level 1) or multiple-choice questions that ask from the learner to choose among a number of answers the right that concerns the result that occur after the demonstration of a problem (at level 3) to open-ended questions that ask to construct a method or to investigate a way for solving a problem (at level 6). Table I presents examples of exercises/ activities that can be provided to a learner according to the revised Bloom's taxonomy level.

IV. Description of the Creation Adaptive Test Algorithm

In this section the algorithm that has been developed for creating adaptive tests using WSM is presented. Log files have to be keeper for both learners and exercises.

❖ For learners:

- **KL**: knowledge level
- **PrK**: prior knowledge on related domain concept
- **LS**: learner's learning style
- **BL**: Bloom's taxonomy level

The values of the above variables have to be defined dynamically by the adaptive educational system at each interaction of the learner with the system.

❖ For exercises:

- **EKL**: the knowledge level that the exercises concerns
- **IDofPrK**: the degree that the learner's previous knowledge influences the ability of the learner to solve the particular exercise.
- **DofV, DofA, DofK**: The degree that the particular exercise is suitable for learners that have visual, auditory and kinesthetic learning style, corespondingly.
- **TE**: the type of exercise (right/wrong, multiple choice, crosswords, fill in the gap, matching exercise, open-ended questions etc).
- **DBL1, DBL2, DBL3, DBL4, DBL5, DBL6**: The degree that the particular exercise is suitable for the 1st (remember), 2nd (understand), 3rd (apply), 4th (analyze), 5th (evaluate) and 6th (create) Bloom's taxonomy level, correspondingly.

The values of the above variables have to be defined by the instructor for each exercise, when s/he inserts the particular exercise to the bank of exercises. The values of IDofPrK, DofV, DofA, DofK, DBL1, DBL2, DBL3, DBL4, DBL5 and DBL6 have to be expressed in exactly the same unit, so that the Weighted Sum Model (WSM) can be applied. Therefore, they are expressed as percentage of 100. In other words, they take values between 0 to 100.

❖ Other notations:

- **T**: the set of exercises that are included into the test
- **n**: the number of exercises of the test
- **e**: an exercise
- **ExT**: a set that includes the types of exercises that the instructor desires to be included into the adaptive test
- **wPrK**: the relative weight of importance of the criterion that is associated with the prior knowledge of the learner in a relative domain concept.
- **WLS**: the relative weight of importance of the criterion that is associated with the learner's learning style.
- **wDBL**: the relative weight of importance of the criterion that is associated with the learner's revised Bloom's taxonomy level.
- **DofLS**: The degree that the exercise is suitable for a learner concerning her/ his learning style.
- **DBL**: The degree that the exercise is suitable for a learner concerning her/ his Bloom's taxonomy level.

The steps that the system follows in order to produce the adaptive test:

1) T=Ø

2) The values of n, ExT, WLS and wDBL are defined by the instructor.

3) The system checks the value of the variable PrK of the learner. If s/he has prior related knowledge, then wPrK = 0, else the system asks the instructor to define the value of wPrK.

4) The system checks the value of the variable PrK of the learner.

5) The system checks the value of the variable LS of the learner. If LS = 'visual', then DofLS =DofV; else if LS = 'auditory', then DofLS =DofA; else if LS = 'kinesthetic', then DofLS =DofV.

6) The system checks the value of the variable BL of the learner. If BL = 'remember', then DBL =DBL1; else if BL = 'understand', then DBL =DBL2; else if BL = 'apply', then DBL =DBL3; else if BL = 'analyze', then DBL =DBL4; else if BL = 'evaluate', then DBL =DBL5; else if BL = 'create', then DBL =DBL6.

7) For each exercise e:

a) The system checks the value of the variable EKL. If EKL≠KL, the system excludes e from the set T and "goes" to the next exercise, otherwise it proceeds to the next step.

b) The system checks the value of the variable TE. If TE ∉ ExT, the system excludes e from the set T and "goes" to the next exercise, otherwise it proceeds to the next step.

c) Apply the WSM to evaluate the suitability of e (eWSM-score) for the particular learner:

$$e^{WSM\text{-}score} = w_{PrK}*IDofPrK + w_{LS}*DofLS + w_{DBL}*DBL$$

8) Sort the exercises in descending order based on the WSM scores (if two or more exercises have the same the WSM score, then they are sorted randomly).

9) Insert the first n exercises into the set T (if the selected exercises are less than n, a related message should be displayed to inform the instructor). The test is ready.

V. Evaluation and Discussion

The aforementioned assessment framework was incorporated in two adaptive e-learning systems and was fully evaluated. The first system is an intelligent tutoring system for foreign language learning while the second is for programming language learning. Both systems hold student models and offer several lessons and exercises for assessment. For the two e-learning systems, a 3-layer evaluation was conducted. More specifically, both systems were evaluated by computer science experts who are faculty members in the Department of Informatics of the University of Piraeus, by instructors of the corresponding field (either foreign language learning or programming) and students. The evaluation by all the population was conducted using the e-SEAT evaluation instrument. E-SEAT [21] is comprised of functional criteria that need to be examined and are the following:

a) Question Editing: This category is extensive and plays a vital role in supporting academics who are generating questions. This category presents features that facilitate the creation of questions within e-assessment tools.

b) Assessment Strategy: it is related to aspects that facilitate easy compilation of tests, especially multiple versions of the same assessment, to reduce the time and effort associated with this type of compilation.

c) Test and Response Analysis: it includes facility to obtain the normal statistics that academics require.

d) Test Bank Database: it is central to any e-assessment tool, it must support the creation and maintenance of both questions and tests.

e) Question Types: This category describes the types of questions supported by the e-assessment tool. Important features of this category are the amount of text that can be input as information for the student is not restricted by a set number of characters, along with the structure of the questions which should be aligned with the assessment strategy adopted for that module. These questions can be adapted to test the higher cognitive levels of Revised Bloom taxonomy.

In the evaluation study, the members who participated are the following: 5 computer science experts (faculty members) from the Department of informatics of the University of Piraeus, 10 instructors of the corresponding field (5 instructors of foreign language learning and 5 instructors of programming languages) and 60 students (30 students are learning foreign languages and 30 students are learning programming languages). The students were given the appropriate hardware along with a brief presentation on how to use each one of the two educational platforms. The students had enough time to spend interacting and completing five lessons with the learning software, while all students had a small break in the middle of the sessions. After the completion of their interaction during the five lessons, all students were given questionnaires to complete with guidance from the evaluators and also their teachers. It was observed that students became familiar easily and very quickly with the educational software, its features and its functionalities. Their interest was undiminished during the whole period of their interaction with the educational application.

The evaluation study was conducted with the use of self-supplemented scale questionnaires incorporating closed questions for the students. For our research, we have used 98 questions as follows: a) 31 questions regarding the "Question editing category", b) 10 questions regarding the "Assessment strategy" category, c) 35 questions regarding the "Test and Response Analysis" category, d) 4 questions regarding the "Test Bank" category, and e) 18 questions regarding the "Question Types category". Table II summarizes a small sample of questions that were asked to the computer science experts and the foreign and programming language instructors after their interaction with both applications. These questions are closed-ended questions and the population can answer either with a positive or a negative answer.

After their interaction with the two systems, all the 60 students were asked to answer four scale questions. These questions follow a 1 to 10 ranking (lower is negative, higher is positive) model, as follows:

1) Rate your learning outcome improvement. (1-10)
2) How accurate are the grades that the system gave you? (1-10)
3) Rate your satisfaction. (1-10)
4) Rate your overall experience. (1-10)

The evaluation results are very promising. All the results depict the high acceptance of the novel framework for adaptive assessment. More specifically, concerning both the intelligent tutoring systems for foreign language learning and programming learning, the computer science experts answered the above questions positively in a percentage of either 80% or 100% (either 4 or 5 faculty members). Furthermore, the instructors of foreign languages and programming also answered the above questions positively in a percentage of either 90% or 100% (either 9 or 10 foreign and programming languages instructors). Concerning the students, 86.66% of students declared that they improved their learning outcome using the e-learning system for foreign language instruction while 90% of students declared that they improved their learning outcome using the e-learning system for programming languages instruction. Also, 93.33% of students stated that the grades which the e-learning system for foreign language instruction delivered are accurate in comparison to 91.66% of them using the latter system. Moreover, 95% of students are satisfied from the e-learning system for foreign language instruction in comparison to 96.66% of them using the latter system. Finally, the students declared that their overall experience is very good in the percentage of 95% for the e-learning system for foreign language instruction in comparison to 93.33% of them for the latter system.

VI. Conclusions and Future Work

In this paper, a novel method for adaptive assessment in e-learning systems has been presented. More specifically, the proposed mechanism takes as input several students' characteristics, such as their knowledge level, related previous knowledge and learning style along with the types of exercises and the desirable learning objective and by applying the multiple-criteria decision analysis and the weighted sum model, it is able to adapt the assessments to the needs and preferences of each student. As such, students are placed in the centre of the educational process and personalized instruction is further promoted by incorporating a qualitative adaptive testing mechanism. For the evaluation of this novel mechanism, a 3-layer experimentation was conducted and showed that adaptive testing using multiple-criteria decision analysis and the weighted sum model is highly beneficial.

It is in our future plans to add more functionalities to our novel mechanism, such as the affect recognition and the social interaction module. The affect recognition functionality can provide the opportunity to adapt the assessment to students based on their affect state while the social interaction module will support the adaptation of exercises to groups of students based on their will to collaborate with peers.

TABLE II. A SAMPLE OF QUESTIONS

	N	***Questions***
Question Editing	1	The system allows the incorporation of question metadata (e.g. categories, keywords, learning objectives, and levels of difficulty).
	2	The system provides tools to do automatic analysis of learner responses
	3	The system supports exporting of questions in non-proprietary, interoperable format from the question bank
Assessment Strategy	4	The systems support random generation of questions from the test bank in multiple versions of the same assessment
	5	The system incorporates branching of questions, depending on learners' responses
	6	The system automatically prompts learners to redo an assessment (with different questions covering the same topics) if they get below a specified percentage.
Test and Response	7	The system displays a comparison of mark data of different groups.
	8	The statistical analysis per assessment supports correlation of assessment data across different class groups.
	9	The system presents discrimination index statistical analysis per assessment.
Test Bank	10	The system draws random questions from a question bank, as required.
	11	The system contains questions which have been moderated for the required standard and cognitive levels.
	12	The system assigns global unique identifiers to all questions created or revised in the question bank.
Question Types	13	The system supports categorizing.
	14	The system supports reordering/rearrangement/sequencing.
	15	The system supports video or audio clips.

REFERENCES

[1] C. Troussas, A. Krouska, and M. Virvou, "Reinforcement theory combined with a badge system to foster student's performance in e-learning environments", in Proc. 8th IEEE International Conference on Information, Intelligence, Systems & Applications (IISA), Larnaca, Cyprus, 2017, pp. 1-6.

[2] J-J Vie, F. Popineau, F. Tort, B. Marteau, and N. Denos, "A Heuristic Method for Large-Scale Cognitive-Diagnostic Computerized Adaptive Testing, Proceedings of the Fourth", in Proc 4th ACM Conference on Learning @ Scale, USA, 2017, pp. 323-326.

[3] C.-H. Chen, and G.-H. Tzeng, "Creating the aspired intelligent assessment systems for teaching materials", Expert Systems with Applications, vol. 38, no. 10, pp. 12168-12179, 2011.

[4] A. Baykasoglu, and Z.D.U. Durmusoglu, "A Hybrid MCDM for Private Primary School Assessment Using DEMATEL Based on ANP and Fuzzy Cognitive Map", Int. J. Comput. Int. Sys., vol. 7, no. 4, pp. 615-635, Sept. 2014.

[5] E. Triantaphyllou, Multi-Criteria Decision Making Methods: A Comparative Study. Norwell, MA: Kluwer, 2000.

[6] S. Klinkenberg, M. Straatemeier, and H.L.J. Van der Maas, "Computer adaptive practice of maths ability using a new item response model for on the fly ability and difficulty estimation", Computers & Education, vol. 57, no. 2, pp. 1813–1824, Sept. 2011.

[7] S. M. Čisar, P. Čisar, and R. Pinter, "Evaluation of knowledge in Object Oriented Programming course with computer adaptive tests", Computers & Education, vol. 92– 93, pp. 142-160, Jan.–Feb. 2016.

[8] H. Ozyurt, O. Ozyurt, A. Baki, and B. B. Guven, "Integrating computerized adaptive testing into UZWEBMAT: Implementation of individualized assessment module in an e-learning system," Expert Systems with Applications, vol. 39, pp. 9837-9847, Aug. 2012.

[9] M. Badaracco, and L. Martinez, "A fuzzy linguistic algorithm for adaptive test in Intelligent Tutoring System based on competences", Expert Systems with Applications, vol. 40, no. 8, pp. 3073–3086, Jun. 2013.

[10] D. Graf, S.Oppl, and A. Eckmaier, "Towards BPM Skill Assessment using Computerized Adaptive Testing", in Proc. 9th Conf. on Subject-oriented Business Process Management, Darmstadt, Germany, 2017.

[11] S. Oppl, F. Reisinger, A. Eckmaier, and C. Helm, "A flexible online platform for computerized adaptive testing", International Journal of Educational Technology in Higher Education, vol. 14, no. 2, pp 1-21, 2017.

[12] Y. M Huang, Y. T. Lin, and S. C. Cheng, "An adaptive testing system for supporting versatile educational assessment", Computers & Education, vol. 52, no. 1, pp. 53 – 67, Jan. 2009.

[13] M. Barla, M. Bielikova´, A. B. Ezzeddinne, T. Kram´ar, M. Simko, and O. Voz´ar, "On the impact of adaptive test question selection for learning efficiency", Computers and Education, vol. 55, no. 2, pp. 846 – 857, Sept. 2010.

[14] K. Chrysafiadi, and M. Virvou, "Dynamically Personalized E-Training in Computer Programming and the Language C", IEEE Trans. On Education, vol 56, no. 4, pp. 385-392, Nov. 2013.

[15] C. Troussas, M. Virvou, A. Vougiouklidou, and K. J. Espinosa, "Automatic misconception diagnosis in multiple language learning over Social Networks", In 4th Fourth IEEE International Conference on Information, Intelligence, Systems and Applications, Piraeus, Greece, 2013, pp. 212-215.

[16] C. Troussas, M.Virvou, and E. Alepis, "Collaborative learning: Group interaction in an intelligent mobile-assisted multiple language learning system", Informatics in Education journal, vol. 13, no. 2, pp. 279-292, 2014.

[17] W. Barbe, Teaching through modality strengths: Concepts and practices. Columbus, OH: Zaner-Bloser. New York: Inc, 1979.

[18] S. Apipah, Kartono, and Isnarto, "An analysis of mathematical connection ability based on student learning style on visualization auditory kinesthetic (VAK) learning model with self-assessment", J. Phys.: Conf. Ser. 983, 2018.

[19] D. R. Krathwohl, (2002) "A Revision of Bloom's Taxonomy: An Overview" , J. Theory Into Practice, vol. 41, no. 4, pp. 212-218, 2002.

[20] M. Raykova, H. Kostadinova, and G. Totkov, "Adaptive test system based on revised Bloom's taxonomy", in Proc. International Conf. on Computer Systems and Technologies, Vienna, Austria, 2011, pp. 504-509.

[21] U. Singh, and M. de Villiers, "An Evaluation Framework and Instrument for Evaluating e-Assessment Tools", the International Review Of Research In Open And Distributed Learning, vol. 18, no. 6, 2017.