An analysis of the Research on Adaptive Learning: The Next Generation of e-Learning

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Abstract: - This study examines the evidence for the effectiveness of adaptive learning and the satisfaction level of students when using this type of learning. It first analyses the different classifications of adaptive learning systems existing in the literature, to focus later on describing some adaptive and intelligent e-learning systems, mainly those included in the groups of Intelligent Tutoring Systems (ITS), Adaptive Hypermedia Systems (AHS) and Intelligent Collaborative Learning systems. Next, the Effect Size (ES) tool is adopted as a standard way to compare the results of one pedagogical experiment to another. ES is used to analyse the effectiveness of some of the systems previously described, in order to demonstrate that adaptive learning can provide significant improvements in the learning process of students. Secondly, the learners' opinion is analysed in order to estimate their satisfaction and to know their preferred mode of studying. Finally, a number of conclusions and future trends are discussed.

Key-Words: - Adaptive learning, E-Learning, Intelligent Tutoring Systems, Intelligent Collaborative Learning, Intelligent Educational Systems, Adaptive Hypermedia Systems, Learning effectiveness.

1 Introduction

In the last years, important studies in the field of learning and training have been carried out in order to adapt the current educational system to the new needs of the Society and the European Higher Education Area (EHEA). In this sense, there are a lot of works in order to define and develop active learning techniques so that the student is the central element of the learning process.

Research suggests that learning characteristics vary for each individual learner and that students prefer to use different types of resources in distinct ways [1]. Besides preferences of students, other aspects, such as goals and level of background knowledge, have also influence on learning effectiveness. All these aspects are particular for each individual student, so an ideal learning system should adapt its performance to the student needs.

Adaptive learning can offer important advantages since it provides students with individual and personalised learning. The students' satisfaction and the effectiveness of the learning process could be improved if the adaptive e-learning system is able to meet the specific learning needs of each student. Thus, this review article deals with adaptive learning; its strength aspects and its potential. Firstly, different adaptive educational systems found in the literature are described and, secondly, their reported results are analysed in order to examine both their effectiveness and the students' satisfaction level when this type of learning is used.

2 Adaptive Learning

The concept of adaptation has been an important issue of research for learning systems in the last few years. Research has shown that the application of adaptation can provide a better learning environment since learners perceive and process information in very different ways [2]. So, the adaptive educational systems are an alternative to the traditional teaching; they can be considered to be the next generation of e-learning. These systems attempt to be more adaptive by building a model of the goals, preferences and level of knowledge of each individual student, and using this model throughout the interaction with the student in order to adapt to his/her needs.

2.1 Problems Interpreting the Literature on Adaptive Learning

Confusion can result from reading the literature; since adaptive educational systems are most often referred as intelligent educational systems. However, these terms are not always considered synonyms. Adaptive systems "attempt to be different for different students and groups of students by taking into account information accumulated in the individual or group student models" [3]; whereas intelligent systems "apply techniques from the field of Artificial Intelligence (AI) to provide broader and better support for the users of Web-based educational systems" [3].

In addition, there is not only one classification for the adaptive learning systems. So, for example, Brusilovsky and Peylo [3] start with the set of classic Adaptive Hypermedia and Intelligent Tutoring technologies and then add the three groups stemmed from Web-inspired technologies: Adaptive Information Filtering, Intelligent Class Monitoring, and Intelligent Collaborative Learning.

On the other hand, according to the different historical streams for adaptive instructional learning, Mödritscher [4] establishes several types of adaptive educational systems including macroadaptive approach, computer-managed instructional systems, intelligent tutoring systems or adaptive hypermedia.

Since most classifications include the two classic categories, Adaptive Hypermedia and Intelligent Tutoring, this paper is focused on them. Besides, the three different technologies for Intelligent Tutoring defined by Brusilovsky and Peylo [3] (curriculum sequencing, interactive problem solving support and intelligent solution analysis) are also taken into account below when describing the systems in the literature review, as well as some web-inspired technologies like those related to Intelligent Collaborative Learning.

2.2 Adaptive and Intelligent E-learning Systems

A full Intelligent Tutoring System (ITS) should be developed to imitate the one-on-one learning process between teacher and student, but adding new facilities and utilities taking advantage of the technology. Therefore, a full ITS should include all the components of the learning process: representing the content, implementing the instructional strategy and providing a mechanism for assessing the student's learning progress [4].

Although many ITS focus only on one or two components of the learning process, there are also some other that implement almost all of them and should be considered as full ITS. It is then difficult to classify them in separate categories.

On the other hand, Adaptive Hypermedia (AH) is inspired by ITS. Adaptive Hypermedia Systems (AHS) try to combine hypermedia-based and adaptive instructional systems. According to Brusilovsky [5], the adaptive hypermedia system should satisfy three criteria: (1) it should be a hypertext or hypermedia system, (2) it should have a user model, and (3) it should be able to adapt using the user model. In many cases this adaptation is made by using AI techniques, so the systems should be considered ITS. Brusilovsky and Peylo [3] call it *curriculum sequencing* technology. Fig.1 shows a classification of adaptive learning systems, which is based on Brusilovsky and Peylo [3].

Among the systems analysed in this paper, ITES [6], Logicando [7], IAELS [8] and the one presented by Kavcic in [9] are good examples of curriculum sequencing technologies. ITES is a web-based system that uses a fuzzy expert system to construct test sheets and learning paths based on the learning status of each student. ITES is based on a conceptual map method [6] used for modelling the relationships among concepts. Logicando is a learning hypermedia with a tutorial component for logic learning addressed to children aged 9-10 years. It uses an expert system and rules to adapt the content to the child knowledge. IAELS [8] is an adaptive e-learning system that incorporates intelligent agents to make personal courses. The *a priori* algorithm is used to find the best learning path for each student. Kavcic [9] describes an adaptive hypermedia educational system that personalises the instructional sequence through a fuzzy user model and linguistic rules for its dynamic updating.

Many adaptive systems focus the adaptation efforts on the assessment (both, exams and self-assessments) instead of on content presentation. For example, SIETTE [10] [11] emulates oral exams and infers student knowledge through adaptive tests; putting questions to the student adapted to his/her current knowledge. Besides, self-assessment tests done with SIETTE can offer hints with the question or provide feedback with the answer, focusing on cognitive diagnosis. In a similar way, Tai, Tsai and Chen [12] use an adaptive learning system for Chinese keyboarding teaching. The adaptive system is based on a combination of Computerised Adaptive Testing (CAT) and Item Response Theory (IRT) in order to select items to be presented to the student, according to his/her estimated individual abilities.

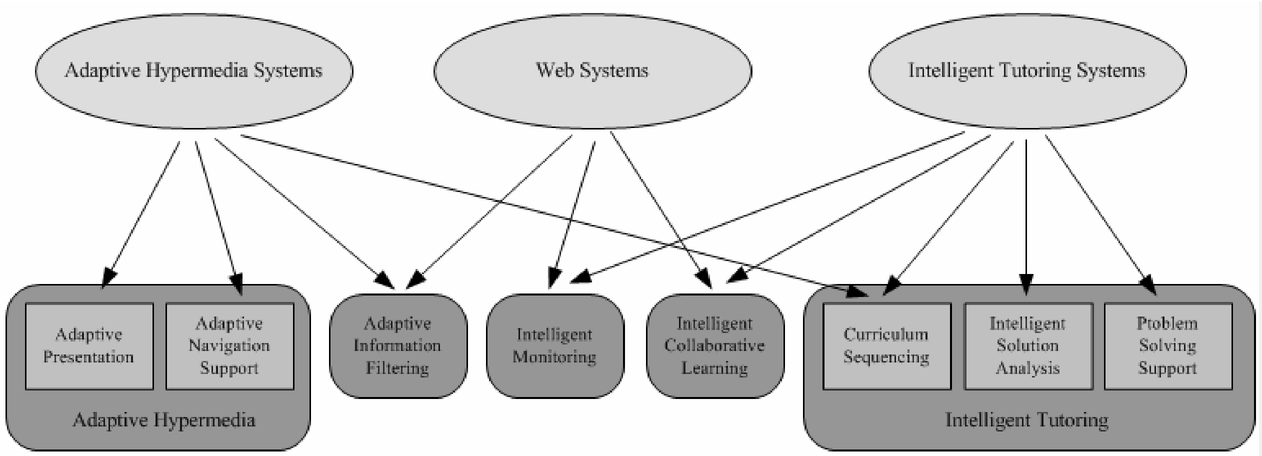

Fig.1. Origin and classification of adaptive learning systems. Source: own elaboration based on Brusilovsky and Peylo [3].

Results of other examples of AHS are also analysed in the following section of this paper. Nirmalakhandan [13] implements an adaptive tutoring system to improve and assess problem-solving skills. HELP [14] is a hypermedia-based English learning system for prepositions that provides adaptive feedback and remedial instructions, through adaptive active hyperlinks, according to the student confidence scores. The confidence scores are diagnosed by the system on the basis of the confidence ratings for each alternative answer indicated by the student when answering a question. Instead a confidence rating, PEL-IRT [15] uses two simple questions as students' feedback: "Do you understand the content of the recommended course materials? (yes or not)" and "what do you think about its difficulty? (very easy, easy, moderate, hard, very hard)". The system applies the maximum likelihood estimation (widely used in CAT domain) to the responses to the first question (comprehension degree) in order to estimate students' ability. Then, it recommends appropriate course materials to the student taking as a base that estimation. The difficulty level of the materials is dynamically adjusted according to a collaborative voting approach that is based on students' feedback information about difficulty. Finally, TANGOW [16] provides a flexible support for the creation of courses with different adaptive features. On the one hand, it adapts the amount of contents to be learnt and, on the other hand, it adjusts the level of the tests to be passed by the student; both according to the student knowledge.

While most of the adaptive systems take decisions using a single source of personalization information, TSAL [17] uses two sources of personalization information: learning behaviour and learning style. TSAL uses the learning style to determine the presentation style (hypermedia, sequential…) and the difficulty levels of materials to be presented. The difficult level of subsequent materials is then adapted according to the learning behaviour, which comprises the learning achievement or outcomes and the time taken to do the tasks (learning efficiency and concentration degree).

Hatzilygeroudis, Giannoulis and Koutsojannis [18] also include both the learning style (theorist, pragmatist and constructivist) and the knowledge level of students in their student model. Their system uses the student model to offer adaptive presentation, adaptive navigation and personalized suggestions about the most appropriate learning path. Besides, a rule-based expert system is used in order to estimate the knowledge level of students.

Own [19] presents an adaptive learning environment that offers two levels of adaptation. At the beginning of the course, students make a Group Embedded Figures Test (GEFT) in order to be classified according to their learning pattern as field-independent or field-dependent. In this way, they are divided into three types of students with three associated learning theories or web-design models: situated model for field-dependent students, constructivist model for field-independent and science college students and scaffolding model for field-independent and non-science college students. Then, each learning system adapts dynamically to the student's progress by means of scenarios or story telling (situated learning system), feedback according to an expert' conceptual map (constructivist system) and scaffolding assisting.

Other more complex systems, like APeLS [20] [21] and aLFanet [22] [23] [24], allow course designers to choose the required adaptation among multiple adaptive options. For example, aLFanet combines user modelling, machine learning and multi-agent technology for multi-scenario intelligent adaptive learning. The adaptive options comprise adaptive contents, adaptive self-assessments and dynamic recommendations (learning objects, assessments, a fellow contribution, additional readings…) for students during the course. Besides, aLFanet uses different sources of personalization information related to the learner profile: previous knowledge level, interest and learning behaviour or progress in the course. APeLS is a personalized e-learning service based on a generic adaptive engine that applies the competence learning space approach in the context of metadata-based reuse of adaptive e-learning resources. This multi-model, metadata driven approach is achieved by: 1) developing a mechanism to model the students, in terms of capturing both their prior knowledge and learning style preferences as well as the knowledge acquired through using personalized courses, 2) selecting, by means of an expert system, an appropriate narrative according to the desired pedagogical approach and 3) creating appropriate metadata for the candidate e-learning resources by describing their adaptive features in order to facilitate the reuse of the elements of adaptability.

As it has been stated before, some ITS approaches take into account more than one aspect of the learning process. For example, Logic-ITA [25] provides curriculum sequencing but also *interactive problem solving support* [3], since it gives intelligent help in each step guiding the student towards the right problem solution. KERMIT [26] is another example of this "double-intelligent" type of systems. KERMIT is an ITS for entity relationship modelling that uses Constraint-Based Modelling to implement the student model and the domain knowledge.

There are other two *interactive problem solving support* systems that are analysed in this paper: Andes [27] and PAT [28]. Andes is an ITS for physics problem-solving. It provides immediate feedback and help in each step, when asked by the student and it can give also unsolicited help for careless mistakes. PAT is another problem solving support system applied in algebra learning.

Hwang [29] also combines two of the ITS technologies, but in this case, besides curriculum sequencing, *intelligent solution analysis* is provided. This type of systems analyse the solution given by an student in order to tell him/her what is wrong or incomplete and what missing concepts could be responsible for an error [5]. CAPIT [30] and the Conceptual Helper [31] also implement this ITS technology taking advantage of Bayesian networks. CAPIT is a normative constraint-based tutor for learning of English punctuation and capitalisation. The students must punctuate and capitalise a fully lowercase; if a constraint is violated, an error message is displayed [30]. In the same way, Conceptual Helper is an ITS for physics conceptual problems that handles the student's misconceptions by showing the correct line of reasoning to describe the phenomena under consideration [31].

The last ITS approaches to be discussed are those included in the group of *Intelligent Collaborative Learning*. Jong et al. [32] use technologies for adaptive group formation and peer help [3]. They follow a grouping strategy based on students' evaluated conceptual graphs, which are calculated using Bayesian analysis. Then, students with complementary concepts of curriculum (i.e. complementary conceptual graphs) are grouped together in order to learn from each other. Besides, for each identified misconception node, the system automatically generates the group learning materials, from a weighted item bank, which will be discussed by the group members. Another example of peer help technology and use of conceptual maps is the Mentor recommender proposed in [33]. Students can initiate a discussion forum about a learning topic (a node in the conceptual map) and the system will offer a list of capable peers (mentors) for solving the question. Chen, Chang and Wang [34] also implement a module for mentor recommending using conceptual maps and student models in a ubiquitous learning web environment that includes also some curriculum sequencing. In this system, beyond the student behaviour and knowledge adaptation, there is a device adaptation in order to support the presentation of learning materials and interaction with students through different devices, from desktop PCs to cell phones or any mobile device.

3 The Evidence for Adaptive Learning

In this section, the adaptive e-learning environments classified in the previous section, are examined in terms of evaluation results: effectiveness and students' opinion when using this type of learning systems.

3.1 Methodology

One important problem determining the effectiveness is deciding when an improvement is significant. The Effect Size (ES) is often used to quantify the effectiveness of a particular intervention, relative to some comparison, for example, between a control group and an experimental group. In fact, ES is a standard way to compare the results of one pedagogical experiment to another.

Reference	Description	Teaching (Grade- Course)
Hwang'03 [6]	Conceptual map model for developing ITS	Primary school – Natural Science
Lanzilotti et al. [7]	Logiocando: Intelligent Tutoring Hypermedia System	Primary school – Logic
Chang et al. [8]	IAELS: Adaptive E-Learning System Based on Intelligent Agents	University – C language
Kavcic [9]	Adaptive Hypermedia Educational System	University – Java
Guzman et al. [10]	SIETTE: Self-Assessment Tests	University – AI&KE
Tai et al [12]	Adaptive Learning System of Learning Chinese Keyboarding Skills	Senior school – Chinese keyboarding
Nirmalakhandan [13]	Adaptive tutorial and assessment approach	University – Hydraulic
Lo et al. [14]	HELP: Hypermedia-based English learning system	University – English
Chen'05 et al. [15]	PEL-IRT: Personalized e-learning system using IRT	University – Neural Network
Muñoz et al. [16]	TANGOW: Adaptive Hypermedia	Secondary school – Mathematics
Tseng et al. [17]	TSAL: Two-source adaptive learning	Secondary school – Mathematics
Hatzilygeroudis et al. [18]	Web-based intelligent education system	University – AI
Own [19]	Adaptive learning Web Course	University – Chemistry
Conlan [20]	APeLS: Adaptive Personalised eLearning Service	University – Database
Van Rosmalen et al. [22]	aLFanet: Adaptive e-learning platform, multiple adaptive scenarios	University – Different courses
Yacef [25]	Logic-ITA Intelligent Teaching Assistant system	University – Computer Science
Suraweera et al. [26]	KERMIT: ITS for Entity Relationship Modelling	University – Database Systems
VanLehn et al. [27]	Andes: ITS for physics problem-solving	U.S. Naval Academy – Physics
Koedinger et al. [28]	PAT: ITS for algebra problem solving	Secondary school – Algebra
Hwang'07 [29]	Gray Forecast Approach	University – Computer Science
Mayo et al. [30]	CAPIT: Normative constraint-based tutor	Primary school – English
Albacete et al. [31]	Conceptual Helper: ITS	University – Mechanics
Jong et al. [32]	Adaptive Mechanism for Grouping Learning Material	University – Electronic Circuits
Wei et al. [33]	Adaptive Mentor in a collaborative learning context	University – Java Programming
Chen'08 et al. [34]	Learning status and peer help in a ubiquitous learning environment	University – Computer Science

Table 1. Adaptive learning systems: Review of literature.

ES places the emphasis on the size of the effect rather than its statistical significance, so it promotes a more scientific approach to the accumulation of knowledge [35].

ES can be measured as the difference in the means of a comparison condition between an experimental group and a control group divided by the pooled standard deviation of the groups. Thalheimer and Cook [36] provide a simplified methodology for calculating ES from published experiments, which has been used in this review.

Cohen [37] suggests that ES of 0.20 are small, 0.50 are medium, and 0.80 are large. However, according to [38], reported improvements in academic achievement should be taken into account, even though the corresponding ES are under the 0.8 limit.

On the other hand, when asking whether adaptive learning is effective and successful, the challenge is to approach the broad range of outcomes to be considered and the difficulty of measuring some of them. Moreover, most researches in the field of adaptive learning do not have data about the improvements obtained in the academic achievement and/or the students' level of satisfaction when using this type of systems.

3.2 Review of Results

In this section, we are going to examine the evidence for the effectiveness of adaptive learning and the students' opinion about this type of learning, since the users (and their degree of satisfaction) are ultimately who will decide whether a system goes to be or not to be successful.

3.2.1 Effectiveness

To assess the learning effectiveness of the different adaptive learning systems, we are going to answer the following question: Can students actually improve their knowledge when the system adapts to their profile and/or performance?

In Table 1, the different adaptive learning systems discussed and described above are summarized in a list together with their main features.

The results of the evaluation of these systems (see Table 2) are analyzed below in order to prove that adaptive learning enhances students' performance.

Starting with the interactive problem solving support systems, results obtained are positive although of different significance. VanLehn et al. [27] show that students who used Andes learned significantly more than control students. The overall ES was somewhat smaller for the final exam (0.25) than for the midterm exams (0.61). The Logic-ITA [25] provides middle to large ES, increasing in different academic years. These values may be also affected by the curriculum sequencing component of the system. The PAT experiments [28] give also different ES for different kind of exams. The most remarkable improvement in this kind of systems could be the usefulness of feedback; since, for example, the ES of this subjective factor is 0.88 in the experiments reported in [26].

Reference	Effect Size
Hwang'03 [6]	1
Lanzilotti et al. [7]	0.1
Kavcic [9]	0.97 – 1.3
Guzman et al. [10]	0.93
Tai et al [12]	0.82
Nirmalakhandan [13]	3.86
Lo et al. [14]	0.78 – 1.14
Muñoz et al. [16]	0.95
Tseng et al. [17]	0.76 – 0.81
Own [19]	0.64
Yacef [25]	0.66 – 1.05
Suraweera et al. [26]	0.15
VanLehn et al. [27]	0.25 – 0.61
Koedinger et al. [28]	0.3 – 1.2
Hwang'07 et al. [29]	1.45
Mayo et al. [30]	0.557
Albacete et al. [31]	0.63
Jong et al. [32]	0.57

Table 2. Reported effect size of the improvement in academic achievement.

Students also achieved a significant improvement compared to control group students with the AHS and the ITS for curriculum sequencing. Table 2 shows that all ES for these systems are large [6] [9] [10] [12] [13] [14] [16] [17] [25] [29], except for the tutoring system described in [7], where results show that children enhanced their knowledge using Logiocando but this enhancement is not significant (ES of 0.1).

One of the most interesting cases to be discussed is presented by Tseng et al. [17]. The authors compare three groups. The first one uses an adaptive system based on student's learning ability and learning style (experimental group). The second one uses the same adaptive system but only based on student's learning ability (control group 1). The last one uses a non-adaptive hypermedia course (control group 2). Statistical analysis results show that the adaptation is helpful for the students in order to improve their learning achievements (with large ES obtained for control group 1 and experimental group when compared with control group 2). Besides, when the two adaptive approaches are compared, the ES is negligible (0.14), indicating that learning style does not affect to students' outcomes in this case. However, the adaptation according to the learning style improves a lot the learning efficiency in terms of learning time (with an ES of 4.91 when comparing experimental group with control group 1).

Adaptive hypermedia technology seems to produce better results when combined with traditional classes [16]. The results of this study show that students that improved the most were those that used the learning system to reinforce contents already studied.

Another interesting result is the one found by Albacete and VanLehn [31]. They examine the effect of adaptive learning according to the previous knowledge and find that students with lower previous knowledge improved more. However, Own [19] finds that in an adaptive learning environment, although students make more progress regardless of their previous knowledge, the difference is significant only for students with more previous knowledge. Since the Conceptual Helper described in [31] includes intelligent solution analysis besides curriculum sequencing, it seems clear that both experiments are not equivalent. In any case, this contradiction is a sign of the fact that experiments and their results should be carefully analysed before extrapolating them, since the systems, the data analysis and the contexts can differ in a significant way.

Regarding the experiments in the case study of adaptive group formation and peer help [32], the calculated ES for the improvement in achievement is 0.57, that is, medium. This is a very good result taking into account that the control and experimental groups only differed in the method of generating the learning materials (by means of the adaptive group learning material generator for the experimental group and randomly generated for the control group), but not in the grouping strategy. Both the experimental and control groups were divided into learning groups via the adaptive grouping. It could be guessed that the ES would have been higher if the grouping strategy would have been intelligent and adaptive only for the experimental group.

The last type of systems within the list in Table 2 is the one that includes intelligent solution analysis. All the reported analysis [29] [30] [31] indicate positive results (from medium to large ES) for these systems.

3.2.2 Learner's opinion

In this section we are going to analyse the learners' opinion in order to answer the following questions: Are students actually satisfied when the e-learning system adapts to their profile, preferences and/or performance? Which students prefer this mode of learning, and why?

Several studies [39] [40] [41] suggest that students' satisfaction is an important factor in order to measure the success or effectiveness of the e-learning process. Moreover, students' satisfaction is associated with students' achievement [42] and it is also a key indicator of educational quality [43]. The satisfaction statistics are necessary for understanding the opinion of learners in relation to every element of the learning process, including contents, methodology and adaptation.

In Table 3, the students' degree of satisfaction with regard to different adaptive educational systems is reported. In all the cases, the students' level of satisfaction has been measured by explicitly asking them for their opinion. The students have had to fill out a survey about what is their level of satisfaction with the use of the adaptive learning system.

Reference	Satisfaction
Chang et al. [8]	0.76
Conejo et al. [11]	0.79
Chen'05 et al. [15]	0.69
Hatzilygeroudis et al. [18]	0.78
Own [19]	0.81
Conlan [20]	0.74
Fuentes et al. [23]	0.50
Suraweera et al. [26]	0.66
VanLehn et al. [27]	0.66
Wei et al. [33]	0.80
Chen'08 et al. [34]	0.76

Table 3. Reported normalized value of students' level of satisfaction.

The questionnaires used to assess the learning efficiency and learning satisfaction of the analysed adaptive systems are based on different scales. Thus, their results have been normalized in Table 3 in order to be able to examine and compare them.

Results show that most learners think that the adaptive educational systems are good for learning and that their requirements are satisfied. Students in the different adaptive learning environments exhibit a mean satisfaction close to 0.7, except for the aLFanet system [23], for which the results show that the learners' level of satisfaction is 0.50 (that is, medium). In any case, this one is a total result, since this system has been used in four universities with different levels of satisfaction: from 0.4 in OUNL (Open University of the Netherlands) to 0.66 in UNED (*Universidad Nacional de Educación a Distancia* – Distance Learning University of Spain). In order to analyse these different results, it is interesting to pinpoint that the activities for evaluating the system were different for each university that participated in the aLFanet project. UNED was responsible for the use phase and thus, more adaptive features were included and more students filled out the questionnaire (25 out of a total of 52 students).

On the other hand, Hatzilygeroudis et al. [18] provide an evaluation of the system with regard to its previous non-adaptive version. The students used the two versions of the system and filled out a questionnaire, which included questions for evaluating their usability and learning. The results showed a slight preference for the adaptive version (of about 15%); although this enhancement was not significant (ES of 0.24).

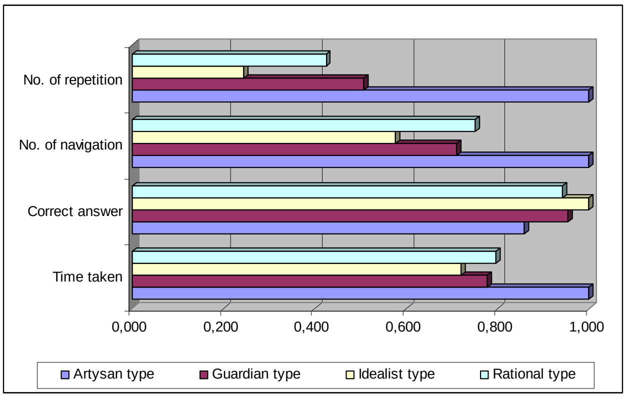

Fig.2. Adaptive hypermedia vs. Personality Type. Source: own elaboration based on data from [44].

Finally, Al-Dujaily and Ryu [44] have researched into the effect of learner's personality on uses and learning performance of adaptive e-learning systems. They follow four categories in order to classify the different learners' personalities: rational type (intuitive thinking, strategic intellect), idealist type (intuitive feeling, diplomatic intellect), artisan type (sensory perception, tactical intellect) and guardian type (sensory judgement, logistical intellect). As it is shown in Fig.2, where, except for correct answer, small value indicates better learning, different personality types obtain different performance on all the measures. The idealist type outperformed the other groups; whereas the artisan type was the most deteriorated. According to the authors [44], "it is probable that the learners with the artisan type tend to seek freedom to act and are concerned with their ability to make an impact on people or situations".

4 Conclusions

In this study different approaches to the problem of adaptive learning and their degree of success have been reviewed in order to analyse their effectiveness from the viewpoint of improvement in academic achievement as well as the students' satisfaction level.

The state-of-the-art of adaptive e-learning covers very specific scenarios with different degree of success. There are many methods and techniques that have been proved to be feasible and useful, but also have shown some pitfalls and problems that need to be resolved.

Many of the reviewed studies rely on detailed, very much time consuming (in terms of codification and design) content with little automatic parameterization. As some correlation between manual elaboration of the content and ES figures can be figured out, one can conclude that adaptive learning is a very manual intensive task. Hence, there are little chances for adaptive learning systems to become mainstream in the general teaching community: when possible, assistance systems and automatic services, all integrated in e-learning tools and platforms, should be provided. Integrating all the phases of the learning process (documentation, tutorship, assessment…) into a unique e-learning context is a pursued goal for many researchers around free open source platforms, like Moodle [45].

On the other hand, there are only a few studies which combine several sources of information about student activity into their model, and even in these cases the information is retrieved from a single instance of the course. Nowadays, student mobility in ubiquitous environments [46] and lifelong learning needs render these approaches too limited.

We would like to finish with some proposals for discussion about open issues that are worth to be explored:

- Extensive logs and generalized achievement tests could be implemented in all activities of the student. Forums, messaging, quizzes, home works and even class attendance should provide standardized data to be processed by different algorithms. Ontologies on those records are to be developed. Metadata and ontologies help teachers to organize all those multiple course materials basing on semantic connections between concepts and make learning resources reusable and searchable for learning and research [47].
- Independent and distributed systems may store and process data about a wider time-window of the learning life of a student. The data would be collected from a wider set of activities and even from different e-learning systems - IMS Learner Information Package (IMS LIP)[1] covers that functionality. This kind of systems, having more significant data, could generate more confident evaluations about competences, knowledge and learning style of students.
- Automatic classification of content and activities based on the interactions of the students and continuous analysis of their achievements will alleviate teacher's requirements. A continuous improvement cycle of content will be possible with this kind of tools.
- Intelligent agents could run AI algorithms with standardized data from a student's LIP and provide adaptive information for the e-learning platform.

[1] http://www.imsglobal.org/profiles/index.html

References:

[1] Kelly, D. and Tangney, B., Adapting to intelligence profile in an adaptive educational system, *Interacting with Computers*, Vol. 18, No. 3, 2006, pp. 385-409.

[2] Lee, M.-G., Profiling students' adaptation styles in Web-based learning, *Computers & Education*, Vol. 36, No. 2, 2001, pp. 121-132.

[3] Brusilovsky, P. and Peylo, C., Adaptive and Intelligent Web-based Educational Systems, *International Journal of Artificial Intelligence in Education*, Vol. 13, 2003, pp. 156-169.

[4] Mödritscher, F., *Implementation and Evaluation of Pedagogical Strategies in Adaptive E-Learning Environments*, Doctoral Study at the Graz University of Technology, 2007.

[5] Brusilovsky, P., *Methods and Techniques of Adaptive Hypermedia, Adaptive Hypertext and Hypermedia*, London: Kluwer Academic Publishers, 1998, pp. 1-43.

[6] Hwang, G-J., A conceptual map model for developing intelligent tutoring systems, *Computers & Education*, Vol. 40, No. 3, 2003, pp. 217-235.

[7] Lanzilotti, R. and Roselli, T., An Experimental Evaluation of Logiocando, an Intelligent Tutoring Hypermedia System, International *Journal of Artificial Intelligence in Education*, No. 17, 2007, pp. 41-56.

[8] Chang, Y-H., Lu, T-Y. and Fang, R-J., An Adaptive E-Learning System Based on Intelligent Agents, *Proc. of the 6th WSEAS International Conference on Applied Computer Science*, 2007, pp. 200-205.

[9] Kavcic, A., Fuzzy User Modeling for Adaptation in Educational Hypermedia, *IEEE Transactions on Systems, Man, And Cybernetics*, Vol. 34, No. 4, 2004, pp. 439-449.

[10] Guzmán, E., Conejo, R. and Pérez-de-la-Cruz, J.L., Improving Student Performance using Self-Assessment Tests, *IEEE Intelligent Systems*, No. 22, 2007, pp. 46-52.

[11] Conejo, R., Guzmán, E., Millán, E., Trella, M., Pérez-De-La-Cruz, J. L. and Ríos, A., SIETTE: A Web-Based Tool for Adaptive Testing,

International Journal of Artificial Intelligence in Education, No.14, 2004, pp. 29-61.

[12] Tai, D. W-S., Tsai, T-A. and Chen, F. M-C., Performance Study on Learning Chinese Keyboarding Skills Using the Adaptive Learning System, *Global Journal of Engineering Education*, Vol. 5, No. 2, 2001, pp. 153-161.

[13] Nirmalakhandan, N., Computerized adaptive tutorials to improve and assess problem-solving skills, *Computers & Education*, Vol. 49, 2007, pp. 1321-1329.

[14] Lo, J-J., Wang, H-M. and Yeh, S-W., Effects of confidence scores and remedial instruction on prepositions learning in adaptive hypermedia, *Computers & Education*, Vol. 42, 2004, pp. 45-63.

[15] Chen, C-M., Lee, H-M. and Chen, Y-H., Personalized e-learning system using Item Response Theory, *Computers & Education*, Vol. 44, No. 3, 2005, pp. 237-255.

[16] Muñoz, F. and Ortigosa, A., Using Adaptive Hypermedia to Support Diversity in Secondary Schools, *Proc. of the 6th International Conference on Advanced Learning Technologies*, 2006, pp. 1055-1059.

[17] Tseng, J. C. R., Chu, H-C., Hwang, G-J., Tsai, C-C., Development of an adaptive learning system with two sources of personalization information, *Computers & Education*, 2007, doi:10.1016/j.compedu.2007.08.002.

[18] Hatzilygeroudis, I. Giannoulis, C. and Koutsojannis, C., Combining Expert Systems and Adaptive Hypermedia Technologies in a Web, Based Educational System, *Proc. of the 5th IEEE International Conference on Advanced Learning Technologies (ICALT'05)*, 2005, pp. 249-253.

[19] Own, Z., The Application of an Adaptive, Web-based Learning Environment on Oxidation-reduction Reactions, *International Journal of Science and Mathematics Education*, Vol. 4, No. 1, 2006, pp. 73-96.

[20] Conlan, O., *The Multi-Model, Metadata driven approach to Personalised eLearning Services*, PhD thesis, University of Dublin, Trinity College, Dublin, Ireland, 2005.

[21] Dagger, D., Conlan, O. and Wade, V., Fundamental Requirements of Personalised eLearning Development Environments, *Proc. of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, 2005, pp. 2746-2754.

[22] Van Rosmalen, P., Vogten, H., Van Es, R., Passier, H., Poelmans, P. and Koper, R., Authoring a full life cycle model in standards-based, adaptive e-learning, *Educational Technology & Society*, Vol. 9, No. 1, 2006, pp. 72-83.

[23] Fuentes, C., Carrión, M. J., Arana, C., Boticario, J. G., Barrera, C., Santos O. C., Van Rosmalen, P., Schmidt, J. A., Hoke, I., Barros, F. and Canada, R., *aLFanet D66 – Evaluation Results*, Project Deliverable Report, 2005. Available at: http://rtd.softwareag.es/alfanet/

[24] Santos, O. C., Boticario, J. G. and Barrera, C., The Standards-based Architecture of the Adaptive Learning Environment aLFanet, *WSEAS Transactions on Computers*, No. 6, Vo1. 3, 2004, pp. 1814-1818.

[25] Yacef, K., The Logic-ITA in the classroom: a medium scale experiment, *International Journal on Artificial Intelligence in Education*, No. 15, 2005, pp. 41-60.

[26] Suraweera, P. and Mitrovic, A., An Intelligent Tutoring System for Entity Relationship Modelling, *International Journal Artificial Intelligent in Education*, Vol. 14, No. 3-4, 2004, pp. 375-417.

[27] VanLehn, K., Lynch, C., Schulze, K., Shapiro, J. A., Shelby, R., Taylor, L., Treacy, D., Weinstein, A. and Wintersgill, M., The Andes Physics Tutoring System: Lessons Learned, *International Journal of Artificial Intelligence in Education*, Vol. 15, No. 3, 2005, pp. 678-685.

[28] Koedinger, K. R., Anderson, J. R., Hadley, W. H. and Mark, M. A., Intelligent tutoring goes to school in the big city, *International Journal of Artificial Intelligence in Education*, Vol. 8, No. 1, 1997, pp. 30-43.

[29] Hwang, G. J., Gray Forecast Approach for Developing Distance Learning and Diagnostic Systems, *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 37, No. 1, 2007, pp. 98-108.

[30] Mayo, M. and Mitrovic, A., Optimising ITS Behaviour with Bayesian Networks and Decision Theory, *International Journal of Artificial Intelligence in Education*, No. 12, 2001, pp. 124-153.

[31] Albacete, P. L. and VanLehn, K. A., Evaluating the Effectiveness of a Cognitive Tutor for Fundamental Physics Concepts, *Proc. of the 22nd Annual Meeting of the Cognitive Science Society*, 2000, pp. 25-30.

[32] Jong, B-S., Chan, T-Y., Wu, Y-L. and Lin, T-W., Applying the Adaptive Learning Material Producing Strategy to Group Learning, *Lecture Notes in Computer Science (LNCS)*, Vol. 3942, 2006, pp. 39-49.

[33] Wei, F-H., Lee, L-Y. and Chen, G-D., Supporting adaptive mentor by student preference within context of problem-solving learning, *Proc. of the 4th IEEE International Conference on Advanced Learning Technologies (ICALT'04)*, 2004, pp. 789-791.

[34] Chen, G. D., Chang, C. K. and Wang, C. Y., Ubiquitous learning website: Scaffold learners by mobile devices with information-aware techniques, *Computers & Education*, Vol. 50, 2008, pp. 77-90.

[35] Coe, R., *It's the Effect Size, Stupid: What effect size is and why it is important*, Annual Conference of the British Educational Research Association, September 2002.

[36] Thalheimer, W. and Cook, S., *How to calculate effect sizes from published research: A simplified methodology, A Work-Learning Research Publication*, 2002. Available at: http://work-learning.com/effect_sizes.htm

[37] Cohen, J., A power primer. *Psychological Bulletin*, No. 112, 1992, pp. 155-159.

[38] Prince, M., Does Active Learning Work? A Review of the Research. *Journal. Engineering Education*, Vol. 93, No. 3, pp. 223-231, 2004.

[39] Bures, E. M., Abrami, P. C. and Amundsen, C., Student motivation to learn via computer conferencing, *Research in Higher Education*, Vol. 41, No. 5, 2000, pp. 593–621.

[40] Swan, K., Shea, P., Fredericksen, E., Pickett, A. and Pelz, W. E., Course design factors influencing the success of online learning, *Proc. of WebNet - World Conference on the WWW and Internet*, 2000, pp. 513–518.

[41] Levy, Y., Comparing dropouts and persistence in e-learning courses, *Computers & Education*, Vol. 48, 2007, pp. 185-204.

[42] Kuh, G. D., Assessing what really matters to student learning: Inside the National Survey of Student Engagement, *Change*, Vol. 33, No. 3, 2001, pp. 10-17.

[43] *National Survey of Student Engagement, Engaged Learning: Fostering Success for All Students*, Annual Report 2006. Available at: http://nsse.iub.edu/NSSE_2006_Annual_Report/docs/NSSE_2006_Annual_Report.pdf

[44] Al-Dujaily, A. and Ryu, H., A Relationship between e-Learning Performance and Personality, *Proc. of the 6th International Conference on Advanced Learning Technologies (ICALT'06)*, 2006, pp. 84-86.

[45] Verdú, E., Regueras, L. M., Verdú, M. J., Pérez, M. A. and de Castro, J. P., Improving the Higher Education through Technology-based Active Methodologies: A Case Study, *WSEAS Transactions on Advances in Engineering Education*, Vol. 3, No. 7, 2006, pp. 649–656.

[46] Kuitunen, P., Honkaranta, A. and Salonen, K., Ontologies and metadata for E-Learning environments in Ecological and Environmental science, *WSEAS Transactions on Advances in Engineering Education*, Vol. 5, No. 1, 2008, pp. 29–42.

[47] Soo-Hwan, K., HyeonCheol, K., Jin-Tae, L., Seon-Kwan, H. and Chul-Hyun L., A Design of u-Learning System based on Memory Theories in Ubiquitous Environments, *WSEAS Transactions on Advances in Engineering Education*, Vol. 5, No. 2, 2008, pp. 77–82.