Is Adaptive Learning Effective? A Review of the Research

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Abstract: - This study examines the evidence for the effectiveness of adaptive learning. It first analyses the different classifications of adaptive learning systems existing in the literature, to focus later on Intelligent Tutoring System (ITS) and Adaptive Hypermedia Systems (AHS) describing some examples of both types of 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 the systems previously described, in order to demonstrate that adaptive learning can provide significant improvements in the learning process of students. Finally, a number of conclusions and future trends are discussed.

Key-Words: - Adaptive learning, E-Learning, Intelligent Tutoring Systems, 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. 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. Thus, this review article deals with adaptive learning and its effectiveness. Firstly, different adaptive educational systems found in the literature are described and, secondly, their reported results are analysed.

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. So, the adaptive educational systems are an alternative to the traditional teaching. 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" [2]; 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" [2].

In addition, there is not only one classification of the adaptive learning systems. So, for example, Brusilovsky and Peylo [2] 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 Collaboration Support.

On the other hand, according to the different historical streams for adaptive instructional learning, Mödritscher [3] 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 [2] (curriculum sequencing, interactive problem solving support and intelligent solution analysis) are also taken into account below when describing the systems in the literature review.

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. [3]

Although many Intelligent Tutor Systems 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 [4], 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 [2] call it *curriculum sequencing* technology.

Among the systems analysed in this paper, ITES [5], Logicando [6] and the one presented by Kavcic in [7] 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 [5] 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. Kavcic [7] 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 [8] 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 with SIETTE can offer hints with the question or provide feedback with the answer, focusing on cognitive diagnosis.

Results of other examples of AHS are also analysed in the following section of this paper. Nirmalakhandan [9] implements an adaptive tutoring system to improve and assess problem-solving skills. HELP [10] 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. TANGOW [11] 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 [12] 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).

As it has been stated before, some ITS approaches take into account more than one aspect of the learning process. For example, Logic-ITA [13] provides curriculum sequencing but also *interactive problem solving support* [2], since it gives intelligent help in each step guiding the student towards the right problem solution. KERMIT [14] 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 [15] and PAT [16]. ANDES is an ITS for physics problem-solving. It gives 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 [17] 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 [4]. CAPIT [18] and the Conceptual Helper [19] 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 [18]. 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 [19].

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.

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.

Effect size 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 [20].

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 [21] provide a simplified methodology for calculating effect sizes from published experiments, which has been used in this review.

Cohen [22] suggests that effect sizes of 0.20 are small, 0.50 are medium, and 0.80 are large. However, according to [23], reported improvements in academic achievement should be taken into account, even though the corresponding effect sizes are under the 0.8 limit.

On the other hand, when asking whether adaptive learning is effective, 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.

3.2 Review of Results

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?

Reference	Description	Teaching (Grade- Course)
Hwang'03 [5]	Conceptual map model for developing ITS	Primary school – Natural Science
Lanzilotti et al. [6]	Logiocando: Intelligent Tutoring Hypermedia System	Primary school – Logic
Kavcic [7]	Adaptive Hypermedia Educational System	University – Java
Guzman et al. [8]	SIETTE: Self-Assessment Tests	University – AI&KE
Nirmalakhandan [9]	Adaptive tutorial and assessment approach	University – Hydraulic
Lo et al. [10]	HELP: Hypermedia-based English learning system	University – English
Muñoz et al. [11]	TANGOW: Adaptive Hypermedia	Secondary School – Mathematics
Tseng et al. [12]	TSAL: Two-source adaptive learning	Secondary school – Mathematics
Yacef [13]	Logic-ITA Intelligent Teaching Assistant system	University – Computer Science
Suraweera et al. [14]	KERMIT: ITS for Entity Relationship Modelling	University – Database Systems
VanLehn et al. [15]	Andes: ITS for physics problem-solving	U.S. Naval Academy – Physics
Koedinger et al. [16]	PAT: ITS for algebra problem solving	Secondary school – Algebra
Hwang'07 [17]	Gray Forecast Approach	University – Computer Science
Mayo et al. [18]	CAPIT: Normative constraint-based tutor	Primary school – English
Albacete et al. [19]	Conceptual Helper: ITS	University – Mechanics

Table 1. Adaptive learning systems: Review of literature.

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.

Reference	Effect Size
Hwang'03 [5]	1
Lanzilotti et al. [6]	0.1
Kavcic [7]	0.97 - 1.3
Guzman et al. [8]	0.93
Nirmalakhandan [9]	3.86
Lo et al. [10]	0.78 - 1.14
Muñoz et al. [11]	0.95
Tseng et al. [12]	0.76 - 0.81
Yacef [13]	0.66 - 1.05
Suraweera et al. [14]	0.15
VanLehn et al. [15]	0.25 - 0.61
Koedinger et al. [16]	0.3 - 1.2
Hwang'07 et al. [17]	1.45
Mayo et al. [18]	0.557
Albacete et al. [19]	0.63

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

Starting with the interactive problem solving support systems, results obtained are positive although of different significance. VanLehn et al. [15] show that Andes students learned significantly more than control students. The overall ES was somewhat smaller for the final exam (0.25) than the midterm exams (0.61). The Logic-ITA [13] provides middle to large effect sizes, increasing in different academic years. These values may be also affected by the curriculum sequencing component of the system. The PAT experiments [16] give also different effect sizes 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 [14].

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 effect sizes for these systems are large [5] [7] [8] [9] [10] [11] [12] [13] [17], except for the tutoring system described in [6], 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. in [12]. 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 effect sizes obtained for control group 1 and experimental group when compared with control group 2). Besides, when the two adaptive approaches are compared, the effect size 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 effect size of 4.91 when comparing experimental group with control group 1).

Adaptive hypermedia technology seems to produce better results when combined with traditional classes [11]. The results of this study show that students that improved the more were those that used the learning system to reinforce contents already studied.

Another interesting result is the one found by Albacete and VanLehn [19]. They examine the effect of adaptive learning according to the previous knowledge and find that students with lower previous knowledge improved more.

The last type of systems within the list in Table 2 is the one that includes intelligent solution analysis. All the reported analysis [17] [18] [19] indicate positive results (from medium to large effect sizes) for these systems.

4 Conclusions

In this study different approaches to the problem of adaptive learning and their degree of success have been reviewed.

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.

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 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.
- 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.

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