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Adaptation provisioning with respect to learning styles in a Web-based educational system: an experimental study

E. Popescu

Software Engineering Department, University of Craiova, 200585 Craiova, Romania

Abstract

Personalized instruction is seen as a desideratum of today's e-learning systems. The focus of this paper is on those platforms that use learning styles as personalization criterion called learning style-based adaptive educational systems. The paper presents an innovative approach based on an integrative set of learning preferences that alleviates some of the limitations of similar systems. The adaptive methods used as well as their implementation in a dedicated system (WELSA) are presented, together with a thorough evaluation of the approach. The results of the experimental study involving 64 undergraduate students show that accommodating learning styles in WELSA has a beneficial effect on the learning process.

Keywords

adaptive educational system, learning style, personalization.

Introduction

The advent of information and communication technologies, in general, and the Internet and Web technologies, in particular, had a great impact on education, making adaptive instruction both possible and required. Possible because technology-enhanced learning systems have the built-in potential of offering individualized learning paths to the students (unlike in case of face-to-face education where it is impossible for teachers to individualize their instruction approach for every student). Required because of the huge amount of information now available on the Web, which can quickly become overwhelming for the learners; in this context, it is essential to help students avoid the cognitive overload by filtering out unnecessary information and offering them a learning experience tailored to their needs. This tailoring can be accomplished with respect to various factors, such as knowledge, interests, goals, background, individual traits and context of work (Brusilovsky & Millan 2007).

In this paper, we base our adaptation on one of the students' individual traits, namely, their learning style, since it is one of the individual differences that play an important role in learning, according to educational psychologists (Popescu 2009a). A widely accepted definition was given by Keefe (1979); according to it, learning style includes cognitive, affective and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with and responds to the learning environment. There has been a great interest in the field over the past 30 years, leading to the proliferation of the proposed learning style models [71 according to Coffield *et al*. (2004)].

However, although research in the learning style area began more than 30 years ago, the development of learning style-based adaptive educational systems (LSAES) only started during the last decade. Even if recently there have been proposed quite a few such systems, there are still many issues requiring clarification. First, researchers' findings regarding the effect of

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Correspondence: Elvira Popescu, University of Craiova, Software Engineering Department, A. I. Cuza 13, 200585 Craiova, Romania. Email: popescu_elvira@software.ucv.ro

adaptation on the learning process are contradictory – some claim that learning styles lead to an increased learning performance (Carver *et al*. 1999; Bajraktarevic *et al*. 2003; Triantafillou *et al*. 2004), enhanced satisfaction (Papanikolaou *et al*. 2003; Triantafillou *et al*. 2004; Sangineto *et al*. 2008) or reduced learning time (Graf & Kinshuk 2007), while others found no such improvements (Mitchell *et al*. 2004; Brown *et al*. 2006, 2007). Another challenge is to decide on the most appropriate taxonomy of learning styles that should be used in a LSAES given the large number of sometimes overlapping models. Furthermore, since all the learning style models have been initially proposed for traditional learning settings, they need to be adapted for use in technology-enhanced environments. Therefore, we can say that Paredes and Rodriguez's statement, although made several years ago, still applies today: 'it still is unclear which aspects of learning styles are worth modeling and what can be done differently for users with different learning styles' (Paredes & Rodriguez 2004).

The aim of this paper is to investigate how courses can be dynamically adapted to the learning preferences of the students and what are the effects of this adaptation. We start with a brief review of existing approaches, summarizing the findings of the experimental results reported in related works. Next, in section 3, we introduce our own approach in the form of adaptation rules and their implementation in a dedicated Web-based Educational system with Learning Style Adaptation (WELSA). Subsequently, in section 4, we describe our evaluation method followed by a presentation of the experimental results obtained (in section 5) and some discussions (in section 6). Finally, the last section of this paper includes concluding remarks and points towards future research directions.

Similar experimental studies in LSAES

As already mentioned in the introduction, the experimental findings regarding LSAES are contradictory. However, the amount of studies that report a positive influence of an adapted learning environment in terms of learning gain, study time or user satisfaction is definitely larger than those reporting no such effect. In fact, to the best of our knowledge, there are only three studies in the latter category, which we briefly present here.

Mitchell *et al*. (2004) report the results of a study involving 64 undergraduate students who followed a Web tutorial on sorting algorithms. First, the students were classified as having field-dependent vs. field-independent preference (Witkin 1962) using the Cognitive Styles Analysis measuring instrument (Riding 1991). Next, they followed two 25-minute tutorial sessions, one using a standard interface and one using a matched/mismatched interface (the students were randomly assigned to one of the two groups). Finally, the students were asked to fill in a questionnaire. The results of the study indicated that there was a clear preference for the standard interface in case of the mismatched students, but no preference in case of the matched students. Also, there was no significant difference between the learning performance of the two groups of students (based on the pre-test and post-test scores). The authors interpreted these results as raising a question over the suitability of creating different interfaces for students with different learning styles. However, they also acknowledge the fact that there could be conceived better adapted interfaces than those used in the study, for which different results might be obtained.

Brown *et al*. (2006) present a study involving 221 undergraduate and postgraduate students who were classified as visual, verbal or bimodal using the Felder–Soloman Inventory of Learning Styles (ILS) (Soloman & Felder 1998). They were then split into three groups: matched (presented with content corresponding to the student's preference), mismatched (presented with content contrary to the student's preference) and neutral (presented with a mix of visual and verbal content). They all followed a Web-based revision guide using Web-based Hierarchical Universal Reactive Learning Environment (WHURLE), and then they took an exam and a multiple-choice evaluation test. Statistical analysis was performed on collected data in order to test several hypotheses. It should be mentioned that the number of students classified as verbal was very small so they were excluded from the statistical analysis. The conclusion of the study was that the use of a matched or mismatched learning content did not influence learning performance in a statistically significant way. However, the authors acknowledge the existence of many uncontrolled variables that could have influenced the study, and in addition, 'it is also possible that, if there was any significant difference to be found, they were so small so as to be obscured by the coarse-grain measures used to assess academic performance in this study'. Another possible explanation could be that the students used in the study have already been unintentionally pre-selected on the basis of their academic ability so we may assume that these students can already learn effectively even when presented with less than optimal opportunities (i.e. a mismatched learning environment), or it could be that other dimensions of learning styles, which were not included in the study, might have a greater influence on the learning process. The final conclusion of the authors is that 'until more evidence is acquired (e.g. from more extensive user trials), it is difficult to draw firm conclusions about the efficacy and validity of using cognitive styles as means of adaptation in adaptive Web-based education systems'. Another experiment reported by the same authors a year later (Brown *et al*. 2007) led to a similar conclusion: no statistically significant differences in learning gain were found between matched and mismatched users in terms of sequential vs. global learning style.

Next, we present two of the studies that report a positive effect of matching the learning course to the learning styles of the student.

Bajraktarevic *et al*. (2003) performed a study involving 21 14-year-old students, who followed a geography course. They were first classified as sequential vs. global by using the ILS questionnaire (Soloman & Felder 1998). Next, they studied two Web-based course modules, one in an adapted form that matched their learning style and one in an adapted form that mismatched their learning style. The scores obtained by the students in the pre- and post-tests were recorded as well as their browsing times. The statistical analysis showed that the students obtained significantly higher scores after the matched session. The study also showed that the browsing times did not significantly differ among the matched and mismatched sessions and that there was no significant correlation between browsing time and the obtained score.

Graf and Kinshuk (2007) performed a study involving 235 students who followed a course on object-oriented modeling using a version of Moodle learning management system (Moodle 2010) extended with adaptation capabilities. The students completed the ILS questionnaire, being classified on three of the four Felder–Silverman model's dimensions (active/reflective, sensing/intuitive, sequential/global) (Felder & Silverman 1988). Next, they were randomly split into three groups: matched, mismatched and standard. The time spent in the system, the number of logins, the number of visited learning activities, the score on assignments, the score on the final exam and the percentage of requests for additional learning objects (LOs) were recorded and analysed. Significant differences were found on the learning time (between matched and mismatched groups and matched and standard groups), the number of logins (between the matched and standard groups) and the number of requests for additional LOs (between the matched and mismatched groups). To sum up, the matched students spent less time in the course but achieved, on average, the same scores as their peers from the other groups. Furthermore, it seems that the students in the matched group were more satisfied with the recommended course than the rest of the students (judging on the smaller number of additional LOs requested). The results confirmed the hypothesis that learning in a matched environment is easier and offers more satisfaction for students than learning in a mismatched environment.

More studies that report a positive influence of the matched learning environment with respect to learning styles include: Barker *et al*. (2000), Carver *et al*. (1999), Graff (2003), Lee *et al*. (2005), Limongelli *et al*. (2009), Papanikolaou *et al*. (2003), Sangineto *et al*. (2008), Triantafillou *et al*. (2004) and Wang *et al*. (2008). It should be mentioned, however, that some of these systems use not only learning style-based but also knowledge level-based adaptation, which means that the results obtained cannot be entirely attributed to the learning style adaptation. Furthermore, the quality of these studies is varied in terms of sample size, experimental design, data analysis procedures and statistical validity.

An interesting and somehow surprising result was obtained by Kelly and Tangney (2006) in the related field of adaptation to various intelligence types. They used 47 13-year-old boys to analyse the influence of adapting courses to intelligence profiles of the learners according to Gardner's Multiple Intelligences model (1993) and Shearer's MIDAS Inventory (1996). The study included also the level of learning activity of the students and showed that the learning gain of the students with medium and high activity levels was not significantly different in case of matched vs. mismatched environments as these students automatically involved themselves in alternative modes of thinking by exploring a number of different resources. However, in case of the low activity students, the learning gain was significantly higher when the students were presented with mismatched resources. The authors explain these findings by the motivational character of challenge and suggest that 'the best instructional strategy is to provide a variety of resources that challenge the learner'. Furthermore, the medium- and high-level activity learners were not influenced by the matched/mismatched approach since they are inherently used to explore a higher number of various resources.

To sum up, the existing body of evidence is not conclusive so more research should be performed in this area. There could be a wide range of reasons for the contradictory results reported starting with the intrinsic complexity of the learning process, the controversial aspects surrounding learning styles up to the particular conditions of each experiment, the type of adaptation provided and the quality and depth of the evaluation. One common trait of the studies reporting no improvements brought up by adaptation is that all use a single learning dimension of the student: field dependence vs. field independence in the case of Mitchell *et al*. (2004), visual vs. verbal in the case of Brown *et al*. (2006) and sequential vs. global in the case of Brown *et al*. (2007). We believe that this approach is quite limiting, and it could have a negative influence on the effects observed. We argue that it is better to use a broad range of learning preferences as summarized in our proposed Unified Learning Style Model (ULSM), which we will introduce in the next section. The more features integrated, the more comprehensive and representative the learner profile and the more targeted the adaptation. To this end, we built a dedicated system (WELSA), based on ULSM, which includes the most suitable adaptation actions, according to the recommendations in the literature.

Adaptivity mechanism in WELSA

Adaptation logic

The first step towards providing adaptivity is selecting a good taxonomy of learning styles since one of the main criticism issues in this field is the existence of a very large number of (partially overlapping) learning style models proposed and no unanimously accepted one. We therefore advocate the use of ULSM, which integrates characteristics from several models proposed in the literature:

- perception modality: visual vs. verbal;
- processing information (abstract concepts and generalizations vs. concrete, practical examples; serial vs. holistic; active experimentation vs. reflective observation, careful vs. not careful with details);
- field dependence vs. field independence;
- reasoning (deductive vs. inductive);
- organizing information (synthesis vs. analysis);
- motivation (intrinsic vs. extrinsic; deep vs. surface vs. strategic vs. resistant approach);
- persistence (high vs. low);
- pacing (concentrate on one task at a time vs. alternate tasks and subjects);
- social aspects (individual work vs. teamwork; introversion vs. extraversion; competitive vs. collaborative);
- coordinating instance: affectivity vs. thinking.

The aforementioned learning preferences were included in ULSM based on a systematic examination of the constructs that appear in the main learning style models and their intensional definitions. In case of similar constructs present under various names in different models, we included the concept only once, aiming for independence between the learning preferences and the least possible overlap. A detailed description of this model, together with its rationale and benefits, can be found in Popescu (2009a). An implicit method for the identification of each student's ULSM dimensions is included in Popescu (2009b).

The second step consists of the creation of adaptation rules for tailoring the e-learning course to the needs of the students with different ULSM preferences. We have conceptualized our course in a hierarchical manner: each chapter contains several sections and subsections and the lowest level subsections contain the elementary LOs described by a comprehensive set of metadata. Further details about the course structure and metadata can be found in Popescu *et al*. (2008). Because of this fine-grained structure, the course can be adapted by annotating, inserting, eliminating, sorting or moving the component LOs. We therefore decided to rely on sorting and adaptive annotation techniques [according to the classification proposed by Brusilovsky (2007)]. The colour of the title indicates the status of the LO with respect to the current student: recommended (highlighted green title), standard (black title) and not recommended (dimmed light grey title).

Nevertheless, the final decision regarding the ordering of accessing the LOs belongs to the student, who may choose to follow the system's recommendations or not.

The adaptation strategies most appropriate for each student's learning style were designed based on the teaching guidelines found in the literature. In what follows, we will give a few examples of these adaptation rules as they are implemented in WELSA.

In case of a specific *perception modality preference*, the recommended action would be to present the learner first with the preferred media type and then with the alternative representation types. Therefore, in case of a learner with a *visual preference*, the LOs will be sorted in the following order: image and/or video followed by text and/or audio (which will be less recommended resources), while in the case of a learner with a *verbal preference*, the LOs will be reversed: text/audio, followed by image/video (which will be less recommended resources). Furthermore, students with a *verbal preference* will be invited to use the communication tools (chat and forum).

In case of a *preference towards abstract concepts and generalizations*, the LOs are sorted such that the illustrative LOs (examples, counter examples, case studies) are presented after the fundamental LOs (concepts, theories, definitions, etc.), which are the recommended (and consequently highlighted) resources. Conversely, in case of a student who has a *preference towards concrete, practical examples*, the LOs will be sorted in the opposite order: first the illustrative (which are the recommended and highlighted resources) and then the fundamental LOs.

In case of a *serial learning preference*, the recommended navigation technique is by means of the 'Next' button, which is consequently highlighted and placed both at the top and bottom of the page in contrast to the less recommended 'Previous' button and 'Outline', which are dimmed and placed only at the top of the page. On the contrary, in case of a *holistic preference*, the recommended navigation tool is the 'Outline', which is hence highlighted and conveniently placed both at the top and bottom of the page. Another difference between the serial and the holistic learners is in their interest towards the related/supplementary information: this is why it is dimmed in the first case and highlighted in the latter.

Similar adaptation rules were proposed for all ULSM learning preferences but will be skipped here because of space constraints.

WELSA adaptation component

In WELSA, students can learn by browsing through the course and performing the instructional activities suggested (play simulations, solve exercises, etc.). They can also communicate and collaborate with their peers by means of the forum and chat. Students' actions are logged and analysed by the system in order to create accurate learner models. Based on the identified learning preferences and the built-in adaptation rules, the system offers students individualized courses. WELSA also provides functionalities for the teachers, who can create courses by means of a dedicated authoring tool.

Technical details regarding the system, including architectural and implementation issues can be found in Popescu *et al.* (2009). The adaptation component queries the learner model database in order to find the ULSM preferences of the current student. Based on these preferences, the component automatically applies the corresponding adaptation rules and dynamically generates the new Web page. These adaptation rules involve the use of LO metadata, which are independent of any learning style; however, they convey enough information to allow for the adaptation decision-making (i.e. they include essential information related to the media type, the level of abstractness, the instructional role, etc.). Next, the Web page is dynamically composed from the selected and ordered LOs, each with its own status (highlighted, dimmed or standard).

Currently, WELSA only accommodates the following seven ULSM characteristics:

- visual vs. verbal;
- abstract concepts and generalizations vs. concrete practical examples;
- serial vs. holistic;
- active experimentation vs. reflective observation;
- careful vs. not careful with details;
- deductive vs. inductive; and
- individual work vs. team work.

We will illustrate the adaptation mechanism with two WELSA screenshots that show the individualized Web

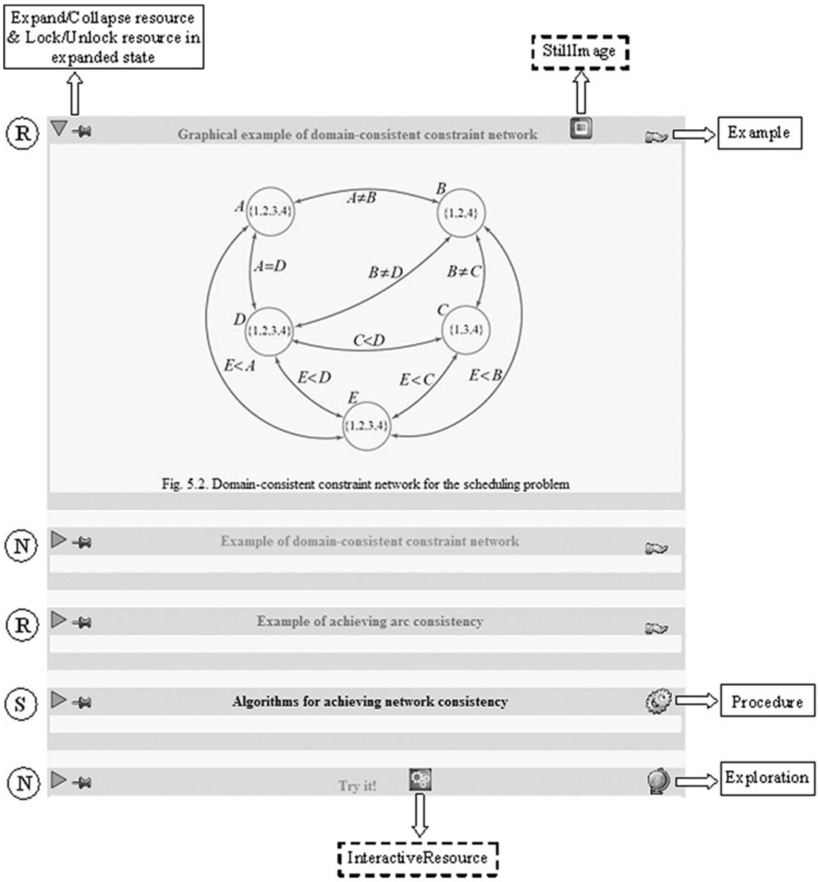

Fig 1 A snapshot from WELSA system with a course page adapted for a student with *visual, concrete* and *reflective observation* preference. Label explanation: boxes on the right-hand side represent the instructional role of the learning object (LO). Dotted boxes at the top and bottom represent the media type of the LO (note that no icon is added in case of text objects). Circles on the left-hand side represent the status of the LO (N, not recommended; R, recommended; S, standard).

pages generated for two students with opposite ULSM preferences.

Figure 1 includes a fragment of an 'Artificial Intelligence' (AI) course page on consistency algorithms for solving constraint satisfaction problems as presented to Student_1, who has a *visual* preference; consequently, the image is marked as recommended and shown in an expanded state. Student_1 also has a preference towards *concrete, practical examples*; hence, the consistency algorithms are first illustrated to him by three examples. The first two examples are equivalent, i.e. they present the same information (domain-consistent constraint networks) in two different media types: image and text, respectively. Therefore, only the first example (in visual format) is recommended to Student_1, while the second example (in textual format) is marked as less recommended. The third example, although in textual format, is marked as recommended since it presents a different type of information (i.e. arc-consistent constraint networks), which should be of interest to Student_1. Once the learner is familiarized with the examples, he is introduced the algorithms for achieving network consistency. The simulation for applying an arc consistency algorithm is subsequently presented, but it is less recommended to Student_1, who has a *reflective observation* preference. However, as mentioned before, these are mere recommendations: Student_1 can choose to consult any LO that he wants and in any order.

Figure 2 includes a fragment of the same course page tailored towards the specific needs of a student with the opposite preferences. Student_2 has an *active experimentation* preference; therefore, she is first advised to try a simulation of an arc consistency algorithm to see how it works. Next, she is invited to test her knowledge, another resource that is suited to her *active* side. Only afterwards is Student_2 presented with the theory behind arc consistency algorithms. Since she also has an *abstract* preference, the algorithms will be more recommended than the examples illustrating the procedure. Furthermore, as Student_2 has a *verbal* preference, the

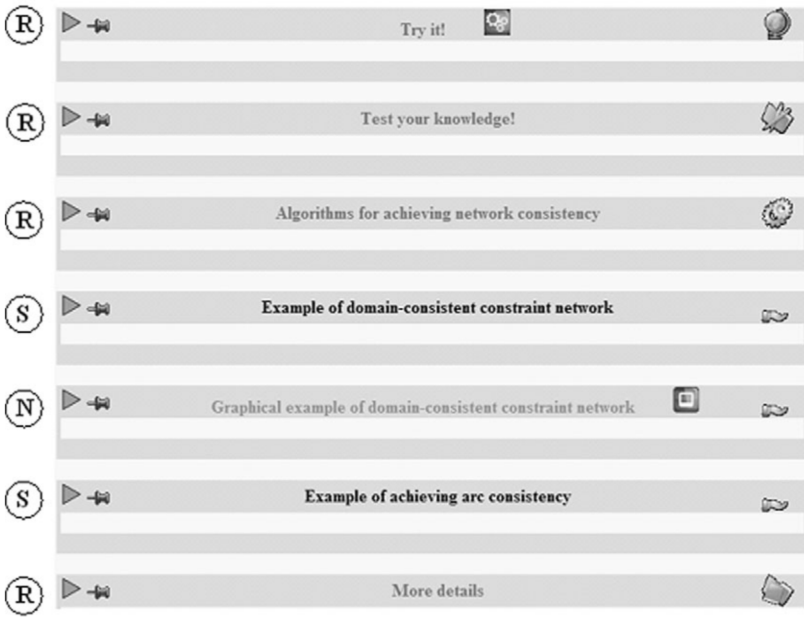

Fig 2 A snapshot from WELSA system with a course page adapted for a student with *verbal, abstract, holistic* and *active experimentation* preference. Label explanation: circles on the left-hand side represent the status of the learning object (N, not recommended; R, recommended; S, standard).

example that is in visual format is less recommended to her. Finally, the additional information regarding arc consistency algorithms ('More details') is highlighted since it is likely to be of interest to the *holistic* Student_2.

Teacher's point of view

WELSA includes a dedicated course editor by means of which the teacher can easily assemble and annotate learning resources, automatically generating the appropriate internal file structure required by the adaptation component. Authors only have to create the actual content and annotate it with a predefined set of metadata (which are independent of any learning style). The adaptation is supplied by the application in the form of the predefined set of adaptation rules described in the preceding Adaptation Logic section. This mechanism reduces the workload of authors, who do not need to be pedagogical experts (neither for associating LOs with learning styles nor for devising adaptation strategies). The only condition for LOs is to be as independent from each other as possible, without cross-references and transition phrases, to insure that the adaptation component can safely apply reordering techniques. Of course, there are cases in which switching the LOs is not desirable; in this situation, the resources should be presented in the predefined order only, independently of the student's preferences (the teacher has the possibility to specify these cases by means of the prerequisites mechanism included in the metadata).

Evidently, the result of the adaptation component is dependent on the suitability of its input (i.e. the quality and variety of the available LOs). Therefore, authors should ideally provide as many equivalent LOs as possible but represented in different media formats, different level of abstractness and formality to cater for various learning preferences. Of course, this might not be always feasible. Just as Gardner said about customizing the learning material to fit the seven intelligence types, 'there is no point in assuming that every topic can be effectively approached in at least seven ways, and it is a waste of effort and time to attempt to do this' (Gardner 1995). However, our AI module (from which the snapshots in the previous subsection were extracted) is an example of a successful case. It was devised starting from an existing course, inspired from the textbook of Poole *et al.* (1998). The authoring process was quite straightforward, and little additional work from the teacher was required (for the LO annotation and for the creation of supplementary videos, animations and interactive simulations). The adaptation results were highly satisfactory as we will see in the next sections.

For the following set of questions, please underline the response of your choice. Please comment on your answers.

Q1. Compare this course session (on "Constraint Satisfaction Problems") with the previous course session (on "Search strategies and solving problems by search").

a) Did you learn: more / the same / less ?

b) Did you enjoy it: more / the same / less ?

c) Did you spend: longer / the same / shorter time?

d) Did you spend: higher / the same / lower learning effort?

e) Did it motivate you: more / the same / less ?

f) Were you: more / equally / less satisfied with the course?

Q2. The course you've just followed contained various types of resources (definitions, algorithms, examples, exercises etc), in different formats (text, images, video, animations). In what order did you generally access these resources?

a) the order in which they were placed in the page (given order)

b) a different order.

Q3. In general, do you prefer:

a) to be recommended a learning path, particular resources, an order of accessing the resources

or b) to choose them by yourself?

Q4. Did you find useful the fact that the resources in the course session you've just followed were marked as recommended / less recommended?

Yes / No

Q5. Did you actually follow these recommendations?

Yes / No

Q6. What was your overall satisfaction with this adapted course session?

Very high / High / Average / Low / Very low

Q7. Would you like to use the adaptive version of WELSA (that you have just experimented) on an everyday basis?

Definitely yes / Probably yes / I can't tell / Probably no / Definitely no

Q8. How important is it for you to have the courses adapted to your learning style?

Very important / Important / Moderately important / Of little importance / Not important

Fig 3 Opinion questionnaire applied to students after the adaptive course session. Note: the answers to the questions Q1, Q6, Q7 and Q8 were coded as ordinal values for further analysis, i.e. for question Q1: 2 = 'more/longer/higher', 1 = 'the same/equally', 0 = 'less/shorter/lower'. For question Q6: 4 = 'Very high', 3 = 'High', 2 = 'Average', 1 = 'Low', 0 = 'Very low'. For question Q7: 4 = 'Definitely yes', 3 = 'Probably yes', 2 = 'I can't tell', 1 = 'Probably no', 0 = 'Definitely no'. For question Q8: 4 = 'Very important', 3 = 'Important', 2 = 'Moderately important', 1 = 'Of little importance', 0 = 'Not important'. Binary answers were considered for the rest of the questions.

Evaluation method

Participants

The experiment involved the participation of 64 undergraduate students in the Computer Science area who were enrolled in an AI course.

Materials

We created a course module in the AI field based on the classical textbook by Poole *et al*. (1998) and implemented it in WELSA. Fragments of the resulted course are presented in Figs 1 and 2. At the end of the course sessions, students had to complete the questionnaire shown in Fig 3.

Procedure

We used the traditional 'with or without' evaluation approach for adaptive systems, i.e. the students followed two course sessions using WELSA: one adaptive and one non-adaptive. In the first session, the students interacted for two hours with the non-adaptive version of WELSA (i.e. with the adaptation mechanism turned off), studying a course chapter on 'Searching and solving problems by search'. For the second two-hour session, the students studied another chapter on 'Constraint satisfaction problems', this time, using the adaptive version of WELSA (i.e. with the adaptation mechanism turned on). Furthermore, in this latter session, the students were randomly split in two equally sized groups: one that was provided with a matched version of the course (further referred to as 'matched group') and one that was provided with a mismatched version of the course (further referred to as 'mismatched group') with respect to the students' learning preferences. It should be mentioned that the students were not aware of the group that they belonged to: they were only told that they will attend a personalized session and were acquainted with the adaptive features used by the system.

After the second session, the students were asked to take a knowledge assessment test and then to fill in a questionnaire, in which they could state their opinion on the course, the learning paths they have taken, the effectiveness of the adaptation, the degree of satisfaction with the course, etc. The full questionnaire is shown in Fig 3.

Since we used the same participants for the adaptive and non-adaptive sessions, we were able to perform both an intra-subject and an inter-subject comparability study. In order to evaluate the adaptation process, we used two kinds of data: the behaviour of the students in WELSA as monitored and logged by the system (objective data) and the students' opinions about the adapted course as stated in the questionnaires (subjective data).

Results

The findings of the objective evaluation (based on the analysis of seven behavioural indicators) were presented in detail in Popescu (2009c). In short, the results obtained were very encouraging: the matched adaptation approach increased the efficiency of the learning process with a lower amount of time needed for studying and a lower number of hits on learning resources (in the context of a similar learning gain). The effectiveness of the matched adaptation and its suitability for addressing students' real needs were also reflected in the higher time spent on recommended vs. not recommended resources as well as the higher number of accesses of those recommended LOs. Finally, the recommended navigation actions were followed to a larger extent than the not recommended ones (Popescu 2009c).

So far, we summarized the objective measures of learner behaviour in the system. Next, we will analyse the students' subjective estimation of these parameters and their perceived effectiveness, efficiency and overall satisfaction.

Perceived difference between adaptive and non-adaptive sessions

The first goal of our questionnaire was to identify the difference between the adaptive and non-adaptive course sessions in terms of learning gain, enjoyment, efficiency, learning effort, motivation and degree of satisfaction as perceived by the students. The results are presented in graphical form in Fig 4, highlighting both the differences between the adaptive and non-adaptive sessions as well as between the matched and mismatched groups. The data were also analysed statistically; Mann–Whitney *U*-test was applied in order to identify the differences between the matched and

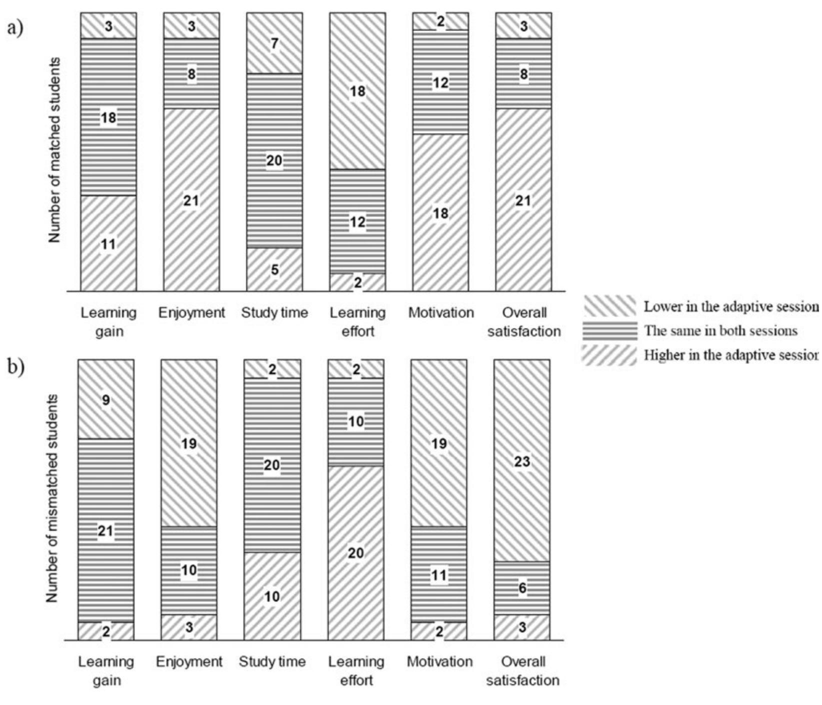

Fig 4 Comparison between the perceived learning gain, enjoyment, study time, learning effort, motivation and overall satisfaction in the adaptive vs. non adaptive sessions: (a) for students in the matched group; (b) for students in the mismatched group.

Table 1. Comparison of students' opinions in matched vs. mismatched groups.

Learning indicator	Matched		Mismatched		U-test
	Median	Mean rank	Median	Mean rank	
Learning gain	1	38.55	1	26.45	318.5*
Enjoyment	2	43.41	0	21.59	163*
Study time	1	28.44	1	36.56	382*
Learning effort	0	21.06	2	43.94	146*
Motivation	2	43.72	0	21.28	153*
Overall satisfaction	2	44.09	0	20.91	141*

$*P < 0.05$.

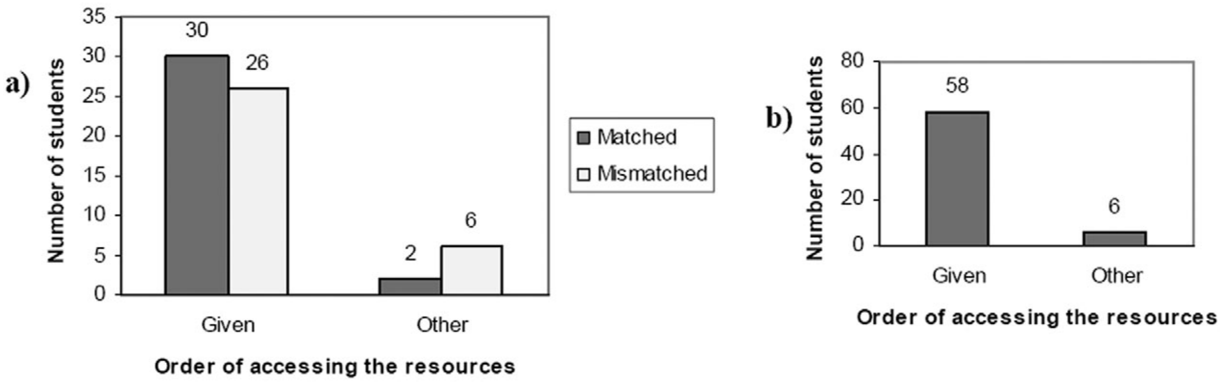

Fig 5 Order of accessing the resources: (a) in the adaptive session; (b) in the non-adaptive session.

mismatched groups. Statistical significance was obtained for all six features, and the results are summarized in Table 1.

According to Fig 4, the majority of the students reported an increase in enjoyment, overall satisfaction and motivation, as well as a decrease in learning effort, after the matched adaptive session (as compared with the non-adaptive session). Conversely, after the mismatched session, the students reported lower levels of overall satisfaction, enjoyment and motivation as well as an increase in the learning effort (as compared with the non-adaptive session). It should be mentioned, however, that the learning gain and study time were reported as similar after the adaptive and non-adaptive sessions by many of the students whether they belonged to the matched or the mismatched learning groups.

Degree of following system's recommendations and perceived usefulness of these recommendations

Next, we were interested in finding out the proportion in which the students followed the system's recommendations and whether they liked the form of these recommendations (i.e. the adaptation techniques that were proposed to them: ordering, resource annotation, etc.). The first question was whether the students chose to access the resources in the order in which they were included in the Web page or in a different one (Q2 in Fig 3). The results are presented in Fig 5a. Of the matched students, 93.75% accessed the resources in the given order as compared with 81.25% of the mismatched students, a difference that was not statistically significant (Fisher's exact test $P = 0.257$, two-tailed).

For the purpose of better understanding and interpreting these results, we should compare them with the preferred order of access as reported by the students after the first (non-adaptive) session (see Fig 5b).

The results are conclusive: the vast majority of the students accessed the learning material in the order in which it was presented to them, both in the non-adaptive and in the adaptive session, be it matched or mismatched. The justifications of the chosen order are quite similar: 'because I thought the course was intentionally ordered in this way', 'because it seemed normal to follow the order proposed by the person who made the course', 'out of convenience', 'I didn't like the fact that the course started with definitions and theory – I would have understood better if there were some examples first. But since this was the order proposed by the teacher, I thought I should follow it.' The fact that the students unthinkingly chose to follow the proposed order because 'teachers know better' despite their own preferences confirms the importance of an appropriate ordering of resources: even if students have the possibility to choose their preferred order, the less experienced ones will rely on the choice already made for them by the course author.

The same preference for being guided is reflected also in the answers to the next question (Q3 in Fig 3). Of the matched students, 87.5% stated that they preferred recommendations and only 12.5% preferred to choose by themselves; conversely, 56.25% of the mismatched students reported a preference towards a recommended path vs. a self-chosen one and 43.75% preferred to choose by themselves. The difference between the two groups was statistically significant (Fisher's exact test $P = 0.011$, two-tailed). Ease of understanding and saving time were highly cited advantages of recommendations in the case of the matched learners. However, most of the students added that the system should only make recommendations, and it is them who should have the final choice: 'It is OK to have a suggested path, but not an imposed one', 'Since at the beginning I don't know anything about the subject, I prefer to have a recommended path. Later on, after I get familiarized with the subject, I may choose the order myself', 'For me it is very useful to have a recommended learning path, because otherwise I get bored very quickly and I don't read anything at all', 'I prefer to have a suggested path, but if I find that it doesn't suit me, then I choose another one'. Only one student pointed out that 'If some resources are not recommended, then they should not have been showed at all'. In case of the mismatched students, the higher preference towards self-chosen paths is probably due to the fact that they associated recommendations with the mismatched ones that they have experienced and consequently, assigned them a negative connotation. This becomes apparent from the students' comments: 'I prefer to choose it myself rather than being given erroneous suggestions', 'I want to choose them myself because no one can know the way I'm thinking'.

Next, we were interested in finding out the degree to which the adaptive annotation technique that we employed was perceived as useful by the students (Q4 in Fig 3). Of the matched students, 81.25% considered the annotation useful as compared with only 15.62% of the mismatched students, a difference that is statistically significant (Fisher's exact test $P < 0.001$, two-tailed). As far as the percentage of the students who actually followed the recommendations is concerned (Q5 in Fig 3), 75% of the matched students reported following them as compared with 31.25% of the mismatched students, a difference that is, again, statistically significant (Fisher's exact test $P < 0.001$, two-tailed).

Overall satisfaction and general attitude towards WELSA and learning styles

Next, we were interested in the overall learner satisfaction and the desire to use WELSA system on an everyday basis (Q6 and Q7 in Fig 3). Furthermore, the level of satisfaction offered by the adaptive system should be corroborated with the level of importance students attribute to learning style adaptation. Indeed, an educational platform is effective only when the features it offers are both valuable and satisfactory for the learners (Levy 2006). We therefore asked the students to assess the importance they grant to having the courses adapted to their learning styles (Q8 in Fig 3). The data were analysed statistically; Mann–Whitney *U*-test was applied in order to identify differences between the matched and mismatched groups, and the results are summarized in Table 2.

As seen from the table, the matched students' overall satisfaction with the adaptive course was significantly higher compared with their mismatched peers. Similarly, the matched students' desire to use WELSA on an everyday basis was significantly higher than that of the mismatched students. However, the difference in terms of importance attributed to learning styles was not statistically significant; the large majority of the students from both groups (90.63% of the matched students and 93.75% of the mismatched students) perceive learning styles as highly important.

Discussion

Taking into account the fact that the amount of time students spent with the platform is limited, we expected the effect of the adaptation to be rather small. Furthermore,

Table 2. Comparisons of matched vs. mismatched students' attitude towards WELSA.

Learning indicator	Matched		Mismatched		U-test
	Median	Mean rank	Median	Mean rank	
Overall satisfaction (Q6)	3	45.48	1	19.52	96.5*
Desire to use the adaptive version of WELSA again (Q7)	3	45.66	1	19.34	91*
Importance attributed to learning style adaptation (Q8)	4	33.69	3	31.31	474

*$P < 0.05$.

as Coffield *et al*. (2004) pointed out, the influence of learning styles on the learning gain of the students is quite modest compared with the influence of other factors such as prior achievement, ability or motivation. We therefore expected an increase in the students' satisfaction rather than an increase in their learning gain.

The results of the experimental study exceeded our expectations, indicating a positive effect that our matched adaptation has on the learning process of the given student sample in terms of lower study time and learning effort as well as an increase in enjoyment, motivation and overall satisfaction. These findings are reflected also in the readiness of the large majority of matched students to adopt WELSA system for large-scale use.

Furthermore, we can conclude from our study that providing students with a course that is contrary to their learning style may hinder their learning (i.e. higher learning effort, lower enjoyment, motivation and overall satisfaction). However, these findings should be interpreted with caution: the student sample was quite limited and only included students who had little experience with Web-based educational systems (and consequently, preferred to be guided during their study). It is therefore possible that more advanced students would know better how to organize their learning paths and would benefit more from the challenging advantages of the mismatched adaptation strategy. Further studies are required to investigate this hypothesis.

The study also underlined the importance of using fragment sorting (i.e. resource ordering), one of the simplest adaptive hypermedia techniques but as it turns out, also one of the most efficient. This technique also implies the least amount of work from the part of the teacher, who only has to ensure that the examples/exercises/simulations, etc. are formulated as independently as possible from the fundamental concepts they complete. This overcomes also one of the disadvantages of the vast majority of textbooks and courses, which are structured in a deductive way, starting with the fundamentals and proceeding to applications (Felder & Silverman 1988). Obviously, there are cases in which changing the order of the learning content is not desirable and does not correspond to the inherent structure of the subject to be taught; in this case, the resources should be presented in the predefined order only, independently of the student's preferences (Popescu 2009c).

Other issues that should be discussed are the 'demand characteristics' (i.e. cues in an experiment that tell the participant what behaviour is expected) (Orne 1959) and the Hawthorne effect (i.e. a short-term improvement caused by observing user performance) (Landsberger 1958). However, it should be noted that the students were not aware of the purpose or expected outcome of the experiment so it is unlikely that they deliberately tried to confirm the researcher's expectations. Furthermore, improvements in the learning process were only reported for one of the two student groups, while contrary findings were reported for the other group (which could not be attributed to the Hawthorne effect). In any case, it would be interesting to conduct the experiments for longer periods of time so that any uncontrolled novelty effects would wear out.

Conclusions

In conclusion, our study found that providing learners with matched courses in WELSA has a beneficial effect on the learning process, while providing them with mismatched courses has a detrimental effect.

Of course, this does not mean that we should fall into the trap of attributing an unjustified importance to learning styles and preferring them to the detriment of other more influential factors, such as reinforcement, student's prior cognitive ability, instructional quality, etc., a danger that Coffield *et al*. (2004) warn us against.

Given the complexity of the learning process, it is indeed very difficult to determine with certainty what percentage of the variance in student performance is attributable to learning styles. We should nevertheless acknowledge the definite increase in the perceived learner satisfaction as resulted from our experiment as well as most of the related studies. We consider that student satisfaction, positive attitude and motivation for learning should be a goal *per se* and that all learning environments should aim at increasing their levels; we argue that accommodating learning styles is a necessary ingredient in this endeavour.

Finally, we do not suggest that constantly matching students' learning preferences is the best approach; undoubtedly, mismatching can have its benefits in terms of boosting motivation and avoiding boredom but more importantly, in terms of helping students develop new learning strategies and improve their weaker learning styles (Grasha 1984; Apter 2001). In this respect, a very interesting discussion about the pros and cons of personalization was provided by Ashman *et al*. (2009). According to them, one of the dangers of adaptation is that it could make information too easily accessible (in a form already understood and preferred by the student), which removes the challenges involved in understanding the material, and it is these challenges that normally lead to the development of valuable meta-cognitive skills (such as internalization, reflection, ability to synthesize knowledge from disparate sources, etc.). The authors conclude that the community's task is to discriminate 'where personalization is useful, where it is harmful and when it is justified by the benefits'. We believe that the work presented in this paper is a step made in this direction.

Further research could be aimed at extending the adaptation component by incorporating an even wider variety of adaptation actions and investigating whether there are some adaptive features that have more impact than others. Of course, care should be taken not to impose any additional overhead on the teachers.

Another direction would be to stop treating learning styles in isolation from the rest of the features in the student profile (knowledge, interests, goals . . .) as most of today's systems do. Integrating all these characteristics would results in a more comprehensive and representative learner profile. Furthermore, the learner features are not independent from each other: the knowledge level, for example, seems to influence the learning preferences of the student. For instance, learners with higher previous knowledge prefer non-restrictive adaptive methods that provide additional information (adaptive annotation, multiple link generation), while students with lower previous knowledge prefer more restrictive adaptive methods that limit their navigation choice (direct guidance, hiding) (Brusilovsky 2003). Consequently, the effect of the adaptation technique is also dependent on the initial competence of the learner as well as his or her level of learning activity as found by Kelly and Tangney (2006). The 'context of work' feature should start being taken into consideration also, given the recent advent of mobile and ubiquitous computing; learners using small screen devices (such as PDAs, smartphones, etc.) would most likely have different learning preferences. Furthermore, other individual differences, such as disabilities and technical background, could be accommodated (Kolias *et al*. 2008), making the educational content accessible to anyone.

Thus, ideally, the adaptive educational systems should not only create a learner profile including as many characteristics as possible but also take into account the interdependences between these characteristics. Some of the related systems mentioned in the second section of this paper already address the former issue by including the knowledge level of the students beside their learning style, e.g. Papanikolaou *et al*. (2003), Sangineto *et al*. (2008) and Limongelli *et al*. (2009); however, none of them addresses the latter.

Finally, the WELSA system could be extended by adding more advanced communication and collaboration functionalities, including social software tools. In this respect, an interesting research direction is to study the possibility of merging WELSA with a so-called personal learning environment, performing also the necessary extensions to the adaptation mechanism (e.g. including collaboration level adaptation techniques). This could be seen as a first step towards the creation of a truly social and adaptive learning environment.

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