

A Unified Learning Style Model for Technology-Enhanced Learning: What, Why and How?

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ABSTRACT: *This paper deals with the use of learning styles in technology-enhanced learning, by introducing a so-called "Unified Learning Style Model" (ULSM). The article aims at providing answers to three main questions: "What is ULSM?", "Why do we need it?" and "How can we use it?". First, a critical analysis regarding learning styles is provided; the identified challenges are addressed by proposing the use of a new model, specifically designed for TEL use. This model integrates learning preferences extracted from several traditional learning style models, related to perception modality, way of processing and organizing information, as well as motivational and social aspects. A detailed description of the ULSM components is provided, together with its rationale and its advantages. The practical applicability of the model is also shown by briefly introducing an adaptive web-based educational system based on it (called WELSA).*

Keywords: Technology-Enhanced Learning, Web-Based Education, User Characteristics, Cognitive Skills, Learning Styles, Individualized Instruction, Learner Modeling, Adaptive Educational Systems

INTRODUCTION

Learning style is a controversial issue both in educational psychology and in the field of adaptive educational systems.

The main reason, which is common to all educational research, is the innate complexity of the learning process (Brown et al., 2007). The factors that affect it are numerous and interconnected: overall IQ, motivation, socio-economic background, time, effort, health, reinforcement, class environment etc. Furthermore, because of the complex nature of learning, it is difficult to isolate the effect of any given factor; due to the numerous uncontrollable variables, the results obtained in an experiment cannot be safely attributed to any particular cause.

There are also some reasons which are specific to the learning style domain. This paper aims at discussing these controversial aspects regarding learning styles, both in traditional and in technology-enhanced learning settings. Furthermore, we try to address some of the identified criticism issues by proposing a Unified Learning Style Model (ULSM), which synthesizes characteristics from the main models in the literature, providing an integrative taxonomy. More specifically, ULSM integrates learning preferences related to perception modality, way of processing and organizing information, as well as motivational and social aspects. An initial proposal of the ULSM has been introduced in (Popescu et al., 2007). Since then, the model underwent a refining and validation process and was successfully used into practice: an e-learning platform called WELSA (**Web-based Educational system with Learning Style Adaptation**) was built on it (Popescu, 2009a; Popescu, 2009b; Popescu, 2009c). In the current paper we present the revised version of ULSM, together with a detailed description of each of its components and the traditional models they were inspired from. We argue that ULSM is the best choice for a learning style based adaptive educational system and we discuss its advantages.

The rest of the paper is structured along the three questions outlined in the title. First we try to motivate **why** there is a need for a Unified Learning Style Model. To this end, in section 2, we present some theoretical aspects, including definitions of learning styles and their implications for pedagogy. Next, in section 3, we discuss the most frequently raised criticisms regarding learning style. As a response to these challenges, we introduce our Unified Learning Style Model. In section 4 we show **what** ULSM is, giving a detailed description of each of its components and outlining its advantages. The next section addresses the final question, namely **how** we can use ULSM in a technology-enhanced learning system and how efficient it is. Finally, the last section contains some conclusions and future research directions.

LEARNING STYLE BACKGROUND

Learning style designates everything that is characteristic to an individual when she/he is learning, i.e. a specific manner of approaching a learning task, the learning strategies activated in order to fulfill the task. A widely accepted definition is 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, which led to the proliferation of proposed approaches. Coffield et al. (2004) identified 71 models of learning styles, among which 13 were categorized as major models, according to their theoretical importance, their widespread use and their influence on other learning style models. These models differ in the learning theories they are based on, the number and the description of the dimensions they include.

Each of the learning style models offers a set of principles and recommendations for the instructional strategies that should be used with the students pertaining to each learning style category. Most psychologists recommend that the teaching style of the instructor should correspond to the learning style of the student (the "matching hypothesis"). Felder (1993) mentions that mismatching can have serious consequences: students may feel "as though they are being addressed in an unfamiliar foreign language. They tend to get lower grades than students whose learning styles are better matched to the instructor's teaching style and are less likely to develop an interest in the course material" (p. 289). Dunn and Griggs (2003) also suggest that teachers adapt the instruction and environmental conditions by allowing learners to work with their strong preferences and to avoid, as far as possible, activities for which learners report having very low preferences.

Some other psychologists support an opposite point of view: using a variety of teaching styles and providing mismatching materials could help avoid boredom and at the same time prepare students develop new learning strategies and improve their weaker learning styles (Apter, 2001; Grasha, 1984).

Another important role of learning styles would be to increase self-awareness of the strengths and weaknesses of the students during the learning process. According to Sadler-Smith (2001), the potential of such awareness lies in "enabling individuals to see and to question their long-held habitual behaviors" (p. 300). Moreover, as Apter (2001) suggests, understanding the various motivational factors in different contexts can "allow people to come more in control" of their motivation and hence of their learning. In addition, the effectiveness of the learning process may improve if students are made aware of the important qualities which they and other learners possess (Coffield et al., 2004).

Despite the importance given by specialists in educational psychology starting 3 decades ago, learning styles have only been introduced relatively recently in technology-enhanced learning. During the last years however, they began to receive special attention, and several learning style based adaptive educational systems (LSAES) started to appear. Most of these systems take a single learning style model into account, such as:

- Felder-Silverman model (FSLSM) (Felder and Silverman, 1988) – which was used in (Bajraktarevic et al., 2003), (Carver et al., 1999), (Cha et al., 2006), (Graf, 2007), (Limongelli et al., 2009), (Sangineto et al., 2008)
- VARK (Flemming, 1995) – which was used in (Gilbert and Han, 1999), (Wang et al., 2008)
- Honey and Mumford model (Honey and Mumford, 2000) – which was used in (Papanikolaou et al., 2003)
- Witkin's field dependence/field independence (Witkin, 1962) – which was used in (Triantafillou et al., 2003).

LEARNING STYLE CRITICISM

Studies in Traditional Learning Settings

The report published by Coffield et al. (2004) is a critical review of the main learning style models that have been introduced in the literature. However it should be noted that the main criticism is addressed at the measuring instruments of the learning style models (which suffer from psychometric flaws), and not at the models themselves. For each of the 13 main models identified, Coffield et al. search and critically analyze the evidence, provided by independent researchers, that the associated instruments could demonstrate internal consistency, test-retest reliability, construct and predictive validity. Only one of them was found to meet all four criteria, while two other models met three criteria; three models met two criteria, four models met only one criterion while the rest of three models met none. This brings us to the idea that an implicit learner modeling method, which is based not on the students' answers to questionnaires but on analyzing their learning behavior, could prove very useful and alleviate the weaknesses of the traditional measuring instruments.

Furthermore, some of the criticism is only related to the limitations of the traditional face-to-face education, given the unrealistic burden it would place on the teachers: "It is hard to imagine teachers routinely changing their teaching style to accommodate up to 30 different learning styles in each class, or even to accommodate four" (Coffield et al., 2004, p. 122). Obviously, this problem is alleviated in e-learning systems, which have the built-in potential of offering individualized learning paths to the students, with little overhead for the teachers.

A further negative aspect outlined in (Coffield et al., 2004) is the theoretical incoherence and conceptual confusion, which come from the multitude of learning style models available. There is a certain degree of overlap among the concepts used, but no direct correspondence between them and no agreed core technical vocabulary. The field suffers from the lack of an overarching synthesis of the main models.

Another weakness of the learning style models is the danger of labeling or pigeonholing the students, since the temptation to classify and stereotype might be difficult to resist.

On the other hand, while pointing out the limitations, Coffield et al. (2004) acknowledge also the benefits of using learning styles, as we have detailed in the previous subsection: self-awareness and metacognition, a lexicon of learning for dialogue, a catalyst for individual, organizational or even systemic change.

Studies in Technology-Enhanced Learning Settings

As far as the field of LSAES is concerned, most of the existing studies reported an improvement in the learning gain and/or student satisfaction: (Bajraktarevic et al., 2003), (Carver et al., 1999), (Graf, 2007), (Lee et al., 2005), (Limongelli et al., 2009), (Papanikolaou et al., 2003), (Sangineto et al., 2008), (Triantafillou et al., 2003), (Wang et al., 2008).

To the best of our knowledge, there are only three studies that reported no improvement brought up by adaptation to learning styles: (Brown et al., 2006), (Brown et al., 2007), (Mitchell et al., 2004). However, as the authors themselves concede, no definitive conclusions can be drawn based on those findings. It could be that better adapted interfaces than those used in the study should be designed, for which different results might be obtained. 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. Or it 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) (Brown et al., 2006).

Finally, a comprehensive review of the current state of the art in relation to quantitative evaluations of learning style personalization in adaptive educational systems is included in (Brown et al., 2009).

Summary of Criticism

To sum up, the most frequently raised criticisms regarding learning styles are:

- There is a very large number of learning style models proposed and there is no unanimously accepted one.
- There is a proliferation of terms and concepts (which sometimes overlap) and there is no mapping between different models (and no agreed taxonomy).
- Dedicated inventories suffer from psychometric weaknesses: some of the instruments used to measure learning styles could not demonstrate internal consistency, test-retest reliability or construct and predictive validity.
- Psychometric instruments can usually be applied only once per student; furthermore it is difficult to motivate learners to fill them out - if they are too long or students are not aware of the consequences or future uses of the questionnaires, they tend to choose answers arbitrarily instead of thinking carefully about them. In addition, the accuracy of self-perceptions is questionable: "self-perceptions can be misleading and the answers are easy to fake if someone is determined to give a misleading impression" (Honey and Mumford, p. 20).
- Learning styles are not a stable cognitive factor over time or over different tasks and situations.

Apart from the criticism regarding learning styles' use in traditional learning, we could also add some issues regarding their use in technology-enhanced learning. The main problem seems to be that the descriptions of the learning style characteristics are only conceived to cover traditional learning aspects. Present theories are only oriented to the classical way of teaching, ignoring technology related preferences. Therefore learning style questionnaires should be revised and adapted to be used in web-based learning systems. They should be enriched with questions oriented towards specific e-learning aspects, not found in the traditional approach.

UNIFIED LEARNING STYLE MODEL - A NEW APPROACH

Rationale

Web-based learning systems that include an implicit and dynamic modeling component alleviate some of the problems identified in the previous section. Indeed, according to many researchers, observations and interviews are more likely than instruments to capture the learning preferences of a student (Coffield et al., 2004). Thus, implicit learner diagnosing based on analyzing students' interactions with the system can prove more accurate, overcoming issues related to the reliability and validity of the questionnaires, as well as their deficiencies regarding technological aspects. The flexible and evolutionary aspects of the learning preferences are also successfully addressed, since the student model is not static, recorded once and for all, but dynamically updated by the system, based on student's changing behavior. The only limitation is that most of the systems based on implicit learner modeling ((Cha et al., 2006), (Gilbert and Han, 1999), (Graf, 2007), (Sangineto et al., 2008), (Stathacopoulou et al., 2007)) are dependent on a particular learning style model. Consequently, they are still subject to the first two weaknesses outlined in the previous subsection.

This issue regarding the multitude of learning style models and their overlapping has been pointed out by many researchers in the field. Cassidy (2004) for example militates for rationalization, consolidation and integration of the more psychometrically robust instruments and models. Gordon and Bull (2004) also call for the use of a "generalized model" or "metamodel", in which they included the overlapping characteristics of six of the four quadrant models. Sternberg (1999) also ascertains that there is no unifying model or metaphor that integrates the various styles, not only between theories, but even within theories.

In this context, our intention is to offer a basis for an integrative learning style model, by gathering characteristics from the main models proposed in the literature. Furthermore, this model is specifically adapted for e-learning settings, by including only those characteristics that meet three conditions: i) have a significant influence on the learning process (according to the educational psychology literature); ii) can be used for adaptivity purposes in a web-based educational system (i.e. the implications they have for pedagogy can be put into practice in a technology-enhanced environment); iii) can be identified from student observable behavior in a web-based educational system. Indeed, not all of the characteristics included in a traditional learning style model can be identified through an e-learning system, nor can they be used for adaptation.

Consequently, we propose a Unified Learning Style Model (ULSM), which includes learning preferences related to:

- 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/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. team work; introversion vs. extraversion; competitive vs. collaborative)
- coordinating instance (affectivity vs. thinking).

The above 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. It should be noted that some of the ULSM preferences have a direct correspondent in one dimension of a learning style model, while others represent just one of the traits that characterize a certain style. For example, the field dependent / field independent ULSM characteristic is taken "as is" from Witkin's (1962) learning style model, including its name and its intensional definition. The active experimentation / reflective observation preference, on the other hand, refers to only a part of the intensional definition of the active / reflective FSLSM dimension (Felder and Silverman, 1988), not including the attraction towards working in teams (or lack thereof). Actually, this latter preference is included as a separate characteristic in ULSM. Finally, the carefulness towards the details is a ULSM preference which doesn't have any direct correspondent in the traditional learning style models, but it is included as a characterizing trait in many of them (e.g. sequential / global or sensing / intuitive dimension of FSLSM).

Description of the Unified Learning Style Model

In what follows we will present for each ULSM characteristic the learning style model it was inspired from, together with its intensional definition.

As far as the perceptual modality is concerned, there are many learning style models that include it: FSLSM (visual / verbal dimension) (Felder and Silverman, 1988), VARK (visual, aural, read/write, kinesthetic) (Flemming, 1995), VAK (visual, auditory, kinesthetic), Dunn and Dunn model (visual, auditory, kinesthetic, tactile) (Dunn and Griggs, 2003), Riding's model (verbaliser / imager) (Riding and Rayner, 1998) etc. We only included the visual versus verbal preference due to the inherent constraints of a web-based learning environment (in which tactile or kinesthetic preferences are more difficult to accommodate). We also retained the intensional definition provided by FSLSM: visual learners remember best what they see (pictures, diagrams, schemas etc) while verbal learners get more out of words, either spoken or written.

In the processing information family we included several preferences: the abstract concepts and generalizations vs. concrete, practical examples was inspired from Kolb's learning cycle (abstract conceptualization / concrete experience) (Kolb, 1999), as well as Gregorc's model (abstract / concrete) (Gregorc, 1985). The students having the first preference rely on conceptual interpretation, while those having the latter preference rely on immediate experience (apprehension) in order to grasp hold of experience.

The serial vs. holistic preference was inspired from FSLSM (sequential / global) and Pask's model (serial / holist) (Pask, 1988). Sequential learners tend to gain understanding in linear steps, while global learners learn in large leaps, being fuzzy about the details of the subject but being able to make rapid connections between subjects.

The active experimentation vs. reflective observation preference was taken from Kolb's learning cycle (active experimentation / reflective observation), being also present in FSLSM (active / reflective) or Honey and Mumford model (activist / reflector) (Honey and Mumford, 2000).

The field dependent vs. field independent preference was taken from Witkin's model, and refers to the proportion in which the surrounding framework dominates the perception of items within it (Witkin, 1962). Field dependent persons may have difficulty to locate the information they are seeking because other information masks what they are looking for ("the forest rather than the trees") and they are more people-oriented. Field independents find it easier to recognize and select the important information from its surrounding field ("the trees rather than the forest") and are more impersonal-oriented.

The inductive vs. deductive preference was taken from the first version of FSLSM: inductive learners prefer to reason from particular facts to a general conclusion; they respond best to problem based learning or inquiry learning; deductive learners prefer to reason from the general to the specific and they like the course to start with the fundamentals and continue with the applications.

The synthetic vs. analytic preference was not taken "as is" from any learning style model. However, similar concepts can be found in Allinson and Hayes' model (intuitive / analytic) (Allinson and Hayes, 1996) and Riding's model (holist / analytic). A synthetic student has an overall image of the subject and tends to combine elements in order to understand the whole; an analytic student focuses on the parts of a whole or on underlying basic principles.

As far as the motivation is concerned, the deep vs. strategic vs. surface vs. resistant approach was inspired from Entwistle's model (Entwistle, 1998), to which the "resistant" component was added, which is similar to Grasha-Riechmann's "avoidant" (Grasha, 1995) and Vermunt's "undirected" (Vermunt, 1998). Students with a deep approach to learning are "meaning-oriented", they want to understand ideas for themselves, they examine logic and argument cautiously and critically and they are actively interested in the course content. Students with a strategic approach are "achieving-oriented", they want to obtain the highest possible grades, being alert to assessment requirements and criteria and gearing work to the perceived preferences of lecturers. Surface learners are "reproducing-oriented", their intention is to pass the exams, they mostly memorize facts, finding difficulty in making sense of new ideas presented, they study without reflecting on either purpose or strategy and they feel undue pressure and worry about work. Resistant learners have a total disinterest towards the course, they refuse to participate to learning activities, they are apathetic and disobedient.

The intrinsic vs. extrinsic motivation approach doesn't have a direct correspondence in a learning style model. It is however related to Entwistle's model, as well as to Apter's telic-paratelic dimension (Apter, 2001). Students who are intrinsically motivated learn for the sake of the experience alone, while those who are extrinsically motivated learn in order to obtain an external reward.

The persistence level was taken from Dunn and Dunn model (persistent / non-persistent): the high persistence students have the inclination to complete tasks, spending a high amount of time studying and coming back to the learning material. The low persistence students have a need for intermittent breaks and they rarely come back to the learning material.

As far as the pacing preference is concerned, it was not taken directly from a learning style model. Students who prefer to concentrate on one task at a time have a linear learning path, with seldom jumps and returns; students who prefer to alternate tasks and subjects like to jump frequently from one passage to another, from one course to another.

The preference towards learning individually versus learning in groups is present "as is" in Dunn and Dunn model (learning groups: learn alone vs. peer oriented), and is also related to many other learning style models (e.g. the FSLSM active / reflective dimension, Herrmann's theorist vs. humanitarian (Herrmann, 1996) etc).

The introvert vs. extravert characteristic is taken from the Myers-Briggs Type Indicator (MBTI) (extraversion / introversion) (Myers and McCaulley, 1985), having correlations with many other models. An introvert learner has the inclination to shrink from social contact and to be preoccupied with internal thoughts and feelings, while an extravert learner has the inclination to be involved with social and practical realities rather than with thoughts and feelings.

The competitive vs. collaborative preference can be found in Grasha-Riechmann's model, being also correlated with Apter's concept of autic mastery (which reflects values of individualism and competitiveness) and alloic sympathy (which reflects values of social belonging and cooperation).

The coordinating instance of the learning process (affectivity vs. thinking) is related to the MBTI's feeling vs. thinking. Students whose learning is coordinated by affectivity like to conclude based on intuition and feeling, while students whose learning is coordinated by thinking take decisions based on analysis, logic and reasoning.

It should be noted that we have only included in ULSM those preferences that can be dealt with in a web-based educational system. Other learning preferences, such as those related to the environment (e.g. noise, light, temperature, comfort) or physical dimensions (e.g. time of the day, intake), can only be catered for in traditional learning settings. Hence, while having an important effect on learning, they are outside the scope of this model.

Of course, learning is so complex that it cannot be completely expressed by any set of learning style dichotomies (Roberts and Newton, 2001). Therefore we do not claim

that our model is exhaustive; we argue however that the above set of characteristics is a first step towards building an integrative, unified model.

Advantages of Our Implicit Modeling Method Using ULSM

Firstly, the problems related to the multitude of learning style models, the concept overlapping and the correlations between learning style dimensions are eliminated.

Secondly, the belonging to a learning style dimension is not absolute; rather it takes the form of a stronger or weaker preference. Thus learners may exhibit characteristics from opposite learning style dimensions in a traditional model, e.g. a student might have a strong preference towards actively working with the educational material while at the same time prefer individual work; in this case, with the traditional approach, she/he would have probably been categorized as "balanced" on the active-reflective dimension of Felder-Silverman learning style model, subsequently being considered to have no preference towards either individual vs. team work or simulations vs. theory; using our proposed approach, she/he would be offered the opportunity to both work individually and interact actively with the material. Consequently, another advantage of the ULSM is a simplified and more accurate student categorization (*feature-based modeling*), as opposed to the traditional *stereotype-based modeling*. In turn, this offers the possibility of finer grained and more effective adaptation actions.

Furthermore, in traditional learning settings, the use of a single learning style model presents the advantage of creating only a limited number of versions of the same course; however, when using technology-enhanced learning, this limitation is removed: the ULSM is able to include a large number of learning preferences, without a substantial increase in the teacher workload. The teacher will have to prepare the same amount of educational materials, which will be dynamically combined according to each student's preferences. Of course, we should point out that not all topics can be taught in all learning styles. 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, p. 206). However, with the use of dynamic adaptation, there is the possibility to accommodate a large number of learning preferences, with little overhead for the teachers, as we have shown in (Popescu, 2009c) and we will see briefly in the next section.

The relative instability of the learning styles is also successfully addressed by our proposed dynamic modeling method, which is based on continuous monitoring and analysis of learner behavioral patterns, as we have shown in (Popescu, 2009a). Thus, unlike in case of one-time applicable questionnaires, where the student model is static, recorded once and for all, in our case the model is dynamically updated by the system, based on student's changing behavior.

Finally, since what we store are individual learning preferences, not styles with a positive or negative connotation, there is no danger of labeling or pigeonholing the student. In addition, due to the implicit diagnosing method and the automatic adaptation process, the learning preferences shouldn't necessarily be revealed to

either the student or the teacher. This would ensure a complete privacy of the learner and avoid the danger of stereotyping. However, an even better approach would be to educate both the students and the teachers to correctly understand and deal with learning styles. Metacognition and learning style awareness can help students understand their strengths and weaknesses in the learning process and use them to their advantage.

PUTTING ULSM TO WORK

So far we have given a detailed description of ULSM, together with its rationale and a theoretical justification of its adoption and its advantages over traditional learning style models. The next step is to give a practical validation of the model, by showing how it can be used in an adaptive educational system and how efficient it is. To this end, we built a dedicated e-learning platform called WELSA (Web-based Educational system with Learning Style Adaptation), based on ULSM. More specifically, WELSA provides students with individualized courses, tailored according to their specific ULSM preferences.

The process takes place in two steps: first accurately identify the learning preferences of the students (learner modeling phase) and secondly apply the corresponding adaptation rules (adaptation phase). As stated in the previous section, what we propose is an implicit and dynamic learner modeling approach, based on analyzing the behavior of the student in WELSA (i.e. the patterns of interaction between the student and the educational system). As far as the adaptation is concerned, WELSA makes use of both adaptive presentation and adaptive navigation support technologies (Brusilovsky, 2007), providing the student with an individualized path through the learning material. The process is fully automated, based on a set of built-in adaptation rules: the course pages are dynamically generated by the system for each student, according to her/his learner model.

An overview of the modeling and adaptation approaches is given in the next two subsections; further details can be found in (Popescu, 2009a) and (Popescu, 2009c) respectively.

The Learner Modeling Approach in WELSA

In user modeling domain, analyzing and interpreting user log files is a valuable source of information about the characteristics of the user (be it interests, preferences, goals etc); also, in the context of e-learning, tracking the interaction of the learner with the educational system has been used as an implicit method for identifying the knowledge level, goals and more recently learning style of the students. This makes sense if we consider that students with different learning styles have different needs and also different behavior during the learning process, according to the proponents of learning style models.

Thus, based on the indications from the literature regarding relevant behavioral patterns (Cha et al., 2006; Garcia et al., 2007; Graf, 2007), as well as our own findings resulted from statistical analysis (Popescu, 2009d), we decided to associate a set of behavioral patterns to each ULSM dimension. (e.g., informally: "A high amount of time spent on contents with graphics, images, video is indicative of a

Visual learning preference" or "A high number of accesses to simulations and other interactive learning resources is indicative of an *Active experimentation preference*"). In order to allow for generalizations, the behavioral patterns that we took into account in our analysis are those that can be obtained from most web-based educational systems (including WELSA). More specifically, these refer to:

- Educational resources (i.e. learning objects - LOs) that compose the course: time spent on each LO, number of accesses to an LO, number of skipped LOs, results obtained to evaluation tests, order of visiting the LOs etc. For each LO, in WELSA we have access to its metadata file, including information regarding the instructional role (e.g. *'Definition'*, *'Example'*, *'Exercise'*, *'Interactivity'*, *'Illustration'* etc), the media type (e.g. *'Text'*, *'Audio'*, *'Image'*, *'Video'*), the level of abstractness and formality etc.
- Navigation choices: either by means of the "Next" and "Previous" buttons or by means of the course Outline
- Communication tools: a synchronous one (chat) and an asynchronous one (forum) – time, number of visits, number of messages.

In order to allow for the collection of all these data, the WELSA Course player was carefully designed, so that all student actions could be monitored and recorded by the system. Next, starting from these raw data (i.e. the student actions and the associated timestamps), the WELSA Analysis tool automatically computes the pattern values for each student. The reliability levels of these patterns are calculated as well (i.e. the larger the number of available relevant actions, the more reliable the resulted pattern). Next, the Analysis tool infers the ULSM preferences of each student, using modeling rules based on the pattern values, their reliability levels and their weights (i.e. the level of influence a pattern has on identifying a learner preference).

It should be noted that these rules also take into account the specificities of each course: the pattern values as well as the importance (weight) of each pattern may vary with the structure and subject of the course. Therefore the Analysis tool has a configuration option which gives teachers the possibility to adjust the predefined values to correspond to the particularities of her/his course or even to eliminate some of the patterns, which are not relevant for that course. The modeling process is formalized and explained in more detail in (Popescu, 2009a).

In order to evaluate the validity of our modeling method, the results obtained by the Analysis tool (implicit modeling method) were compared with the reference results obtained by applying the ULSM questionnaire (explicit modeling method). The experimental study involved 71 undergraduate students in the field of Computer Science, who studied an Artificial Intelligence course module implemented in WELSA. The evaluation was performed for a subset of 12 of the ULSM learning preferences, for which relevant data were available. Good precision results were obtained, with an average accuracy of 75.70%, as reported in (Popescu, 2009a).

The Adaptation Mechanism in WELSA

Once the learning preferences of the students are identified, the next step is to associate the appropriate adaptation rules, which best serve learners with each ULSM preference. The development of these adaptation rules was a delicate task,

since it involved interpretation of the learning style literature in order to identify the prescriptive instructional guidelines. Starting from these teaching methods (which only include a traditional learning view), enhancing them with e-learning specific aspects (technology related preferences) and inspiring from other works that deal with learning style based adaptation (as mentioned in the second section), we extracted the adaptation rules for our LSAES.

One observation is in place here: due to the different nature of the characteristics included in ULSM, not all of them lend themselves to a matching adaptation strategy. In case of motivation for example, it is clear that a surface or a resistant approach should not be encouraged. Therefore the pedagogical action that should be taken is not adaptation, but rather increasing student's metacognition as well as teacher's awareness regarding students' weaknesses in the learning process. In what follows however we will only address those ULSM characteristics that lend themselves to a matching adaptation strategy.

Our pedagogical goal was to offer students recommendations regarding the most suited learning objects and learning path, but let the students decide whether they want to follow our guidelines or not. Offering control to students has several advantages: first of all, in case the learning style preference identified by the system is not accurate, the students can ignore the system recommendations and consult the learning objects that they feel are most suitable for them and in the order that they judge appropriate. Second, there may be students who prefer to study the course extensively and so they should have access to all the additional learning objects. Furthermore, imposing a course structure or order to a student may make them feel frustrated and/or confused, especially when they have a chance to compare their version of the course with their peers'. Finally, in the context of an experimental study (as is our case), allowing the student to choose whether to follow our recommendations or not gives us a measure of the success of our adaptation (i.e. whether the adaptation corresponds to the actual needs of the students).

Due to the above reasons, we decided to rely on sorting and adaptive annotation techniques rather than direct guidance or hiding/removing fragments (according to the classification proposed in (Brusilovsky, 2007)). We also decided to use the popular "traffic light metaphor", to differentiate between recommended LOs (with a highlighted green title), standard LOs (with a black title, as in case of the non-adaptive version of WELSA) and not recommended LOs (with a dimmed light grey title).

Figure 1 illustrates the generation of an Artificial Intelligence course page, individualized for a student with preferences towards *Verbal* perception modality, *Concrete*, *practical examples* and *Reflective observation* (as identified in the modeling phase). The adaptation process is automatically performed by the WELSA Adaptation component. This component starts from the course structure defined by the teacher in the XML course and chapter files, and fills it with the corresponding LOs (as referenced in the metadata files), while ordering and annotating them.

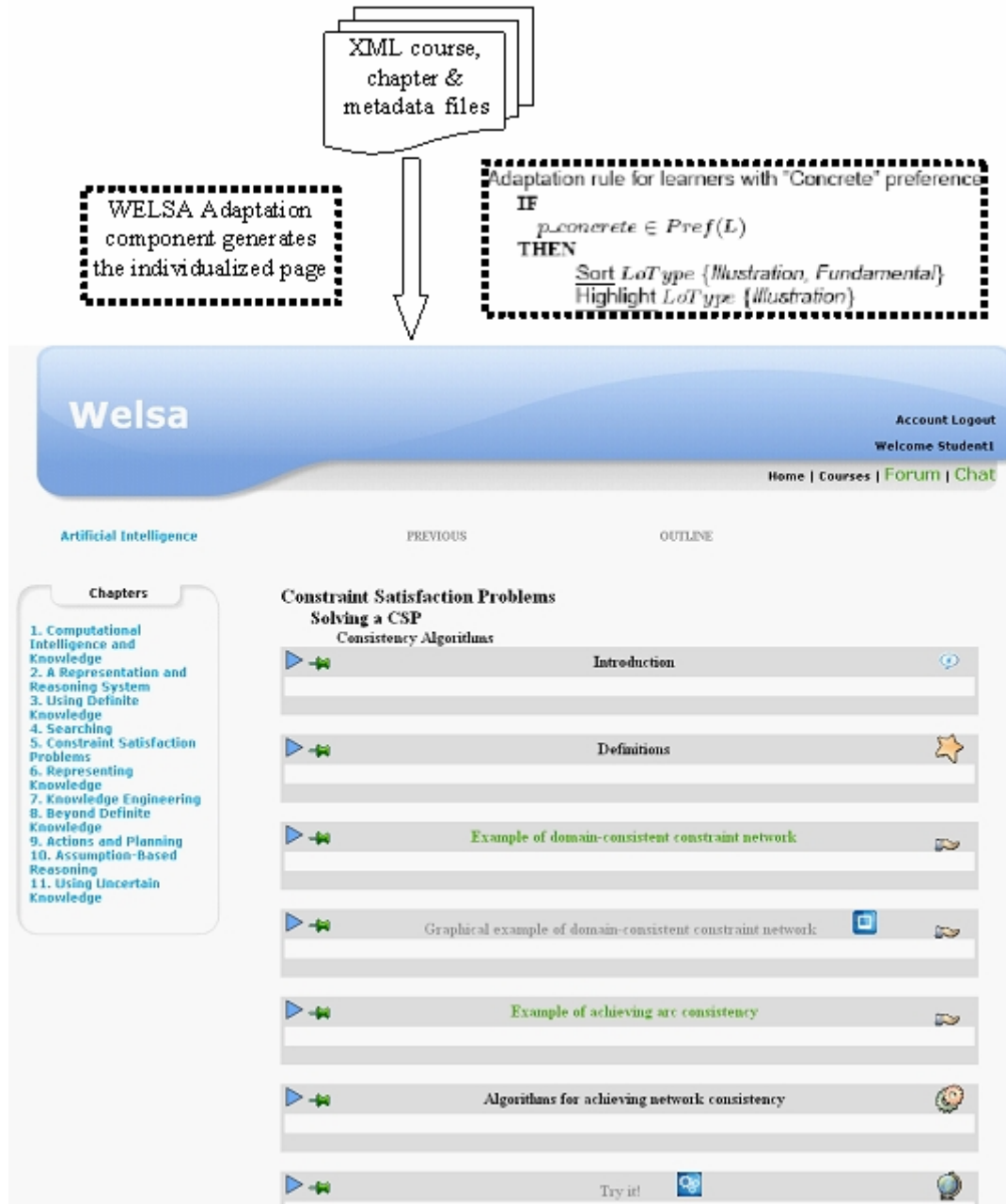


Figure 1. WELSA – dynamic adaptation example

In order to help with the creation of the XML file, a course authoring tool is provided for the teacher, as illustrated in fig. 2 (the example corresponds to the course page from fig. 1). It should be noted that WELSA course editor does not deal with the creation of actual content (text, images, simulations etc) – a variety of existing dedicated tools can be used for this purpose (text editors, graphics editors, HTML editors etc). Instead, WELSA course editor provides a tool for defining the course structure (specifying the order of resources, assembling learning objects in pages, subsections and sections) and adding metadata to existing learning resources. It is important to mention that these metadata are independent of any particular learning style. Instead, they include general information related to the media type, the level of abstractness, the instructional role of the LO, the hierarchical and prerequisite relationships between LOs etc. This lies at the basis of the dynamic adaptation

mechanism, with the adaptation rules making extensive use of metadata. An example of such a rule corresponding to the *Concrete* learning preference is included in Figure 1 (relying on the instructional role of the LO, denoted "LoType"). In addition, this mechanism reduces the workload of authors, who only need to annotate their LOs with standard metadata and 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.

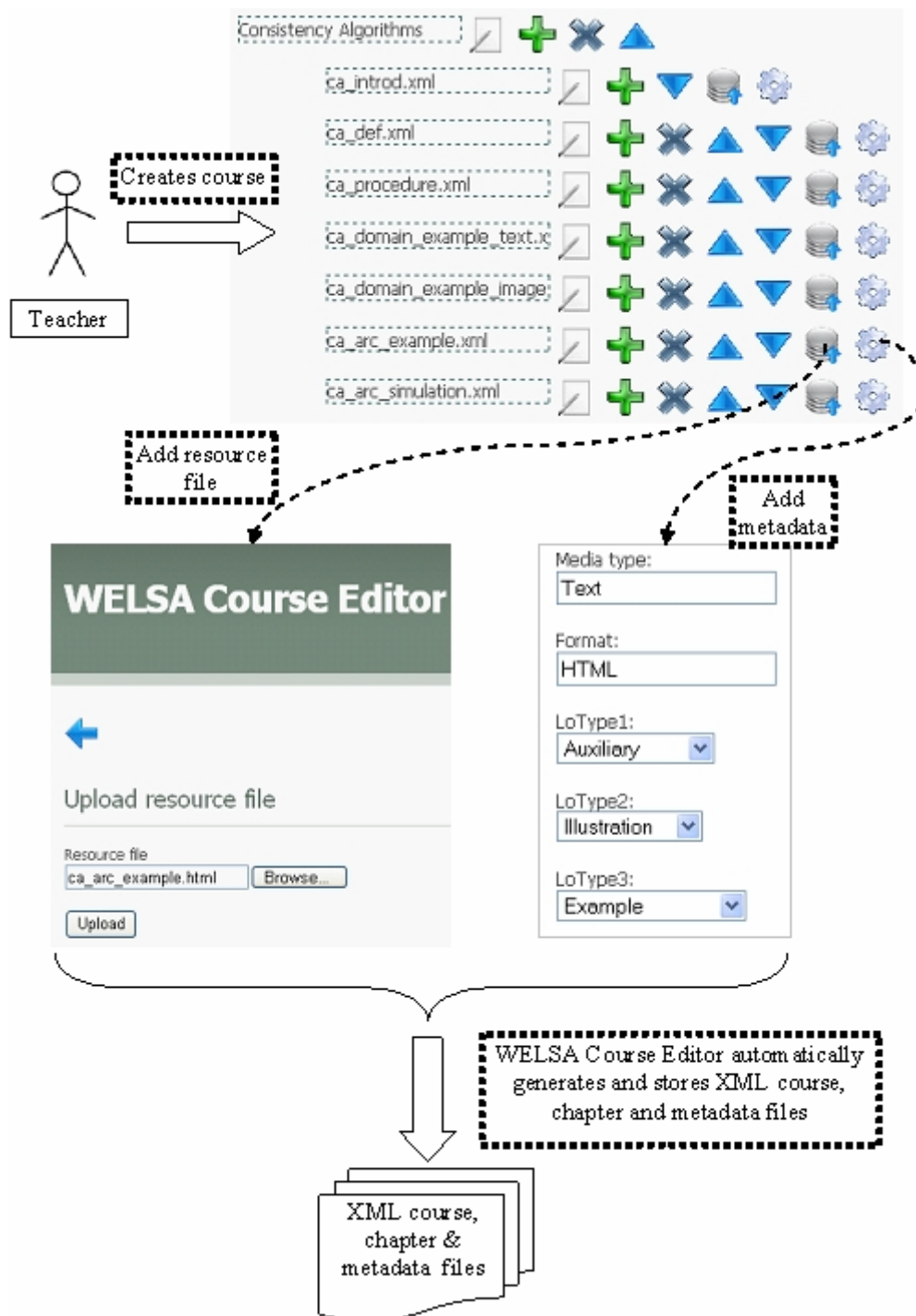


Figure 2. WELSA – course authoring example

When a new page request is received, 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 applies the corresponding adaptation rules and generates the new HTML page from the XML structure files. Thus the web page is composed from the selected and ordered LOs, each with its own status (highlighted, dimmed or standard). In our case, since the current student has a preference towards *Concrete, practical examples*, the algorithms (LO 6 in fig. 1) are first illustrated to her by means of 3 examples, 2 of which are also highlighted as recommended (LOs 3 and 5). Furthermore, since she also has a *Verbal* perception modality, the example which is in graphical format (LO 4) is marked as less recommended and placed after the equivalent text-based example (LO 3). Finally, since the student has a preference towards *Reflective observation*, the interactive simulation (LO 7) is placed at the end of the page and marked as less recommended.

The **validity and effectiveness** of our adaptation approach were empirically confirmed by means of an experiment involving 64 undergraduate students in the field of Computer Science. The students were split in two groups: one which was provided with a matched version of the course (further referred to as "matched group") and one which was provided with a mismatched version of the course (further referred to as "mismatched group"), with respect to the students' learning preferences.

The objective evaluation consisted in performing a statistical analysis on the behavioral patterns exhibited by the students, comparing the values obtained for the matched and mismatched groups in order to find significant differences. t-test was applied when the data were normally distributed and u-test when data did not follow a normal distribution (the normality was checked with the Kolmogorov-Smirnov test). Due to space constraints, we only report here the conclusions of this analysis (a detailed presentation of the results is included in (Popescu, 2009c)): 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 randomly accessed educational resources (lower level of disorientation). The effectiveness of the matched adaptation and its suitability for addressing students' real needs are also reflected in the statistically significant higher time spent on recommended versus not recommended resources, as well the higher number of accesses of those recommended learning objects. Finally, the recommended navigation actions were followed to a larger extent than the not recommended ones.

As far as learners' subjective evaluation of the system is concerned, the students in the matched group reported significantly higher levels of enjoyment, overall satisfaction and motivation, compared to their mismatched peers.

The overall results of the experimental study are very promising, proving the positive effect that our adaptation to learning styles has on the learning process. It should be mentioned also that this experiment was performed with second year students, who had little experience with web-based educational systems and therefore preferred to be guided during their study. Perhaps more advanced students would know better how to organize their learning path and would also benefit from the challenging advantages of the mismatched adaptation strategy. Further studies are required to validate this hypothesis.

CONCLUSIONS

In this paper we provided a critical analysis of learning styles and their use in technology-enhanced learning settings. As a response to the criticism, we introduced a unified learning style model and theoretically justified its use.

However, our intention was not to propose yet another learning style model, but to provide a pragmatic approach, summarizing those learning preferences that could have a practical use in TEL. We therefore showed how the ULSM model was successfully integrated into a dedicated web-based adaptive educational system (WELSA) and reported the encouraging experimental results obtained so far.

Nevertheless, in order to allow for generalization, the system should be tested on a wider scale, with users of variable age, field of study, background knowledge and technical experience. We therefore plan to repeat the experiments for longer periods of time and with a larger and more diverse student sample.

A very challenging research direction would be the individualization of the adaptive techniques to the characteristics of the students (knowledge level, technical background, experience with AES). Several studies suggest that the student knowledge level as well as her/his previous experience with web-based educational systems may have an influence on the effect of the adaptation technique used (Brusilovsky, 2003). For example, students 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). The solution could be the creation of a meta-adaptive system, that should adaptively select the adaptation technology that is the most appropriate for the given student and context. The meta-adaptive system should be able to dynamically improve its decisions, by learning from observing the results obtained with each technology used.

Due to the advent of mobile e-learning applications, ULSM could be further refined to incorporate mobility-related characteristics (i.e. preference towards learning while sitting, standing or moving). Another future research work is to study the applicability of our ULSM model to the new generation of Web 2.0 Personal Learning Environments; in this new context, identifying and performing the necessary extensions to the learner modeling and adaptation mechanisms would also be a challenging research direction.

REFERENCES

- Allinson, C., & Hayes, J. (1996). The Cognitive Style Index. *Journal of Management Studies* 33, 119–135.
- Apter, M.J. (2001). *Motivational Styles in Everyday Life: a Guide to Reversal Theory*. American Psychological Association, Washington.
- Bajraktarevic, N., Hall, W., & Fullick, P. (2003). Incorporating learning styles in hypermedia environment: Empirical evaluation. In: *Proc. Workshop on Adaptive Hypermedia and Adaptive Web-Based Systems*, pp. 41–52.
- Brown, E., Brailsford, T., Fisher, T., Moore, A., & Ashman, H. (2006). Reappraising Cognitive Styles in Adaptive Web Applications. In: *Proc. WWW 2006*, pp. 327–335. ACM Press, New York.

- Brown, E., Fisher, T., & Brailsford, T. (2007). Real Users, Real Results: Examining the Limitations of Learning Styles within AEH. In: *Proc. HT 2007*, pp. 57–66. ACM Press, New York.
- Brown, E., Brailsford, T., Fisher, T., & Moore, A. (2009). Evaluating Learning Style Personalization in Adaptive Systems: Quantitative Methods and Approaches. *IEEE Transactions on Learning Technologies* 2(1), 10-22.
- Brusilovsky, P. (2003). Adaptive Navigation Support in Educational Hypermedia: the Role of Student Knowledge Level and the Case for Meta-Adaptation. *British Journal of Educational Technology* 34(4), 487-497.
- Brusilovsky, P. (2007). Adaptive Navigation Support. In: Brusilovsky, P., Kobsa, A., Nejd, W. (eds.) *Adaptive Web 2007*. LNCS, vol. 4321, pp. 263–290. Springer, Heidelberg.
- Carver, C.A., Howard, R.A., & Lane, W.D. (1999). Enhancing student learning through hypermedia courseware and incorporation of student learning styles. *IEEE Transactions on Education* 42, 33–38.
- Cassidy, S. (2004). Learning Styles: An Overview of Theories, Models and Measures. *Educational Psychology* 24(4), 419–444.
- Cha, H.J., Kim, Y.S., Park, S.H., Yoon, T.B., Jung, Y.M., & Lee, J.H. (2006). Learning styles diagnosis based on user interface behaviors for the customization of learning interfaces in an intelligent tutoring system. In: Ikeda, M., Ashley, K.D., Chan, T.-W. (eds.) *ITS 2006*. LNCS, vol. 4053, pp. 513–524. Springer, Heidelberg.
- Coffield, F., Moseley, D., Hall, E., & Ecclestone, K. (2004). *Learning Styles and Pedagogy in Post-16 Learning. A Systematic and Critical Review*, Learning and Skills Research Centre, UK.
- Dunn, R., & Griggs, S. (2003). *Synthesis of the Dunn and Dunn Learning Styles Model Research: Who, What, When, Where and So What - The Dunn and Dunn Learning Styles Model and Its Theoretical Cornerstone*. St. John's University, New York.
- Entwistle, N.J. (1998) Improving Teaching through Research on Student Learning. In: *University teaching: international perspectives*. Garland, New York.
- Felder, R.M., & Silverman, L.K. (1988). Learning and teaching styles in engineering education. *Engineering Education* 78(7), 674–681. Preceded by a preface in 2002, <http://www4.ncsu.edu/unity/lockers/users/f/felder/public/Papers/LS-1988.pdf>
- Felder, R.M. (1993). Reaching the Second Tier: Learning and Teaching Styles in College Science Education. *College Science Teaching* 23(5), 286–290.
- Flemming, N.D. (1995). I am different; not dumb. Modes of presentation (V.A.R.K.) in the tertiary classroom. In: *Research and development in higher education. Procs. HERDSA 1995*, vol. 18, pp. 308–313.
- Garcia, P., Amandi, A, Schiaffino, S. & Campo, M. (2007). Evaluating Bayesian Networks' Precision for Detecting Students' Learning Styles. *Computers & Education* 49(3), 794-808.
- Gardner, H. (1995). Reflections on multiple intelligences: Myths and messages. *Phi Delta Kappan* 77(3), 200-209.
- Gilbert, J.E., & Han, C.Y. (1999). Adapting instruction in search of 'a significant difference'. *Journal of Network and Computer Applications* 22(3), 149–160.
- Gordon, D., & Bull, G. (2004). The Nexus Explored: A Generalised Model of Learning Styles. In: *Proc. of Society for Information Technology and Teacher Education Intl. Conf.*, pp. 917–925.
- Graf, S. (2007). *Adaptivity in Learning Management Systems Focussing on Learning Styles*. PhD Thesis, Vienna University of Technology, Austria.
- Grasha, A.F. (1984). Learning Styles: the Journey from Greenwich Observatory (1796) to the College Classroom (1984). *Improving College and University Teaching* 32(1), 46–53.
- Grasha, A.F. (1995). *Practical Applications of Psychology*. HarperCollins, New York.
- Gregorc, A.F. (1985). *Style Delineator: A Self-Assessment Instrument for Adults*. Gregorc Associates Inc., Columbia.
- Herrmann, N. (1996). *The Whole Brain Business Book*. McGraw-Hill, New York.
- Honey, P., & Mumford, A. (2000). *The learning styles helper's guide*. Peter Honey Publications Ltd., Maidenhead.
- Keefe, J. (1979). Learning Style: An Overview. In: *NASSP's Student Learning Styles: Diagnosing and Prescribing Programs*, pp. 1–17.
- Kolb, D.A. (1999). *The Kolb Learning Style Inventory*, Version 3. Hay Group, Boston.
- Lee, C.H.M., Cheng, Y.W., Rai, S., & Depickere, A. (2005). What Affect Student Cognitive Style in the Development of Hypermedia Learning System? *Computers & Education* 45, 1–19.
- Limongelli, C., Sciarone, F., Temperini, M., & Vaste, G. (2009). Adaptive Learning with the LS-Plan System: A Field Evaluation. *IEEE Transactions on Learning Technologies* 2(3), 203-215.

- Mitchell, T., Chen, S.Y., & Macredie, R. (2004). Adapting Hypermedia to Cognitive Styles: Is It Necessary? In: *Proc. Workshop on Individual Differences in Adaptive Hypermedia in AH 2004*, pp. 70–79.
- Myers, I.B., & McCaulley, M.H. (1985). *Manual: A Guide to the Development and Use of the Myers-Briggs Type Indicator*. Consulting Psychologists Press, Palo Alto.
- Papanikolaou, K.A., Grigoriadou, M., Kornilakis, H., & Magoulas, G.D. (2003). Personalizing the interaction in a Web-based educational hypermedia system: the case of INSPIRE. *User- Modeling and User-Adapted Interaction* 13, 213–267.
- Pask, G. (1988). Learning Strategies, Teaching Strategies, and Conceptual or Learning Style. In: *Learning strategies and learning styles*, pp. 83–100. Plenum Press, New York.
- Popescu, E., Trigano, P., & Badica, C. (2007). Towards a Unified Learning Style Model in Adaptive Educational Systems. In: *Proc. ICALT 2007*, pp. 804–808. IEEE Computer Society Press, Los Alamitos.
- Popescu, E. (2009a). Diagnosing Students' Learning Style in an Educational Hypermedia System. In: *Cognitive and Emotional Processes in Web-based Education: Integrating Human Factors and Personalization*. Advances in Web-Based Learning Book Series, IGI Global, pp. 187–208.
- Popescu, E. (2009b). Addressing Learning Style Criticism: The Unified Learning Style Model Revisited. In: Spaniol, M., et al. (eds.) *Proc. ICWL 2009*. LNCS, vol. 5686, pp. 332–342. Springer, Heidelberg.
- Popescu, E. (2009c). Evaluating the Impact of Adaptation to Learning Styles in a Web-based Educational System. In: Spaniol, M., et al. (eds.) *Proc. ICWL 2009*. LNCS, vol. 5686, pp. 344–353. Springer, Heidelberg.
- Popescu, E. (2009d). Learning Styles and Behavioral Differences in Web-based Learning Settings. In: *Proc. ICALT 2009*, pp. 446–450. IEEE Computer Society Press, Los Alamitos.
- Riding, R.J., & Rayner, S. (1998). *Cognitive Styles and Learning Strategies: Understanding Style Differences in Learning and Behaviour*. David Fulton Publishers.
- Roberts, M.J., & Newton, E.J. (2001). Understanding Strategy Selection. *Intl. Journal of Computer Studies* 54, 137–154.
- Sadler-Smith, E. (2001). The Relationship between Learning Style and Cognitive Style. *Personality and Individual Differences* 30, 609–616.
- Sanginetto, E., Capuano, N., Gaeta, & M., Micarelli, A. (2008). Adaptive course generation through learning styles representation. *Universal Access in the Information Society* 7(1), 1–23.
- Stathacopoulou, R., Grigoriadou, M., Samarakou, M., & Mitropoulos, D. (2007). Monitoring students' actions and using teachers' expertise in implementing and evaluating the neural network-based fuzzy diagnostic model. *Expert Systems with Applications* 32, 955–975.
- Sternberg, R.J. (1999). *Thinking Styles*. Cambridge University Press, Cambridge.
- Triantafillou, E., Pomportsis, A., & Demetriadis, S. (2003). The design and the formative evaluation of an adaptive educational system based on cognitive styles. *Computers & Education* 41, 87–103.
- Vermunt, J.D. (1998). The Regulation of Constructive Learning Processes. *British Journal of Educational Psychology* 68, 149–171.
- Wang, T., Wang, K., & Huang, Y. (2008). Using a Style-based Ant Colony System for Adaptive Learning. *Expert Systems with Applications* 34(4), 2449–2464.
- Witkin, H.A. (1962). *Psychological differentiation: studies of development*. Wiley, Chichester.