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Dynamic adaptive hypermedia systems for e-learning

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Dynamic adaptive hypermedia systems for e-learning

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Chapter 1

Introduction

The first section of this chapter describes the motivation, background and problem statement of our thesis. Next the main research issues are outlined. The last section presents the structure of the thesis.

1.1. Motivation

E-learning is a very dynamic domain, in continuous growth, which refers to educational content or learning experiences delivered or mediated by means of digital technologies. The development of this domain is expected to lead to a growth in the quality of instruction, cost reductions and a more efficient implementation of distance and life-long learning. Today's e-learning is dominated by the Learning Management Systems (LMS), such as Blackboard (Blackboard, 2008), Moodle (Moodle, 2008), ATutor (ATutor, 2008) or dotLRN (dotLRN, 2008); these represent integrated systems which offer support for a wide area of activities in the e-learning process. Thus teachers can use LMS for the creation of courses and test suites, for communicating with the students, for monitoring and evaluating their work. Students can learn, communicate and collaborate by means of LMS.

The problem is that LMS don't offer personalized services, all the students being given access to the same set of educational resources and tools, without taking into account the differences in knowledge level, interests, motivation and goals. As (Morrison et al., 2001) stated: "Just as people differ in many respects, so do ways in which they learn differ. Some of these differences are evident in the kinds of experiences each person requires to learn and, if competence in a skill is to be acquired, in the amount of time and practice each person needs. It is essential, therefore, early in the planning process, to give attention to the characteristics, abilities, and experiences of the learners - both as a group and as individuals." Adaptive educational hypermedia systems (AEHS) try to offer an alternative to the non-individualized approach, by providing various services adapted to the learner profile. The purpose of this adaptation is to maximize the subjective learner satisfaction, the learning speed (efficiency) and the assessment results (effectiveness).

There are two basic questions in AEHS:

- "What can we adapt to?" - The answer includes several learner characteristics, such as knowledge, goals, tasks or interest, background and experience, learning style, context and environment.

- "What can be adapted?" - The answer includes the presentation (adapting the actual content, the presentation of that content, or the media used) as well as the navigation (adapting the link anchors that are shown, the link destinations, the overviews for orientation support).

Identifying the learner characteristics represents the first stage of adaptation, called learner modeling. Adaptation decision making is the second stage, in which particular adaptation actions are taken, based on the information gathered in the first stage. The process is schematically illustrated in Fig.1.1.

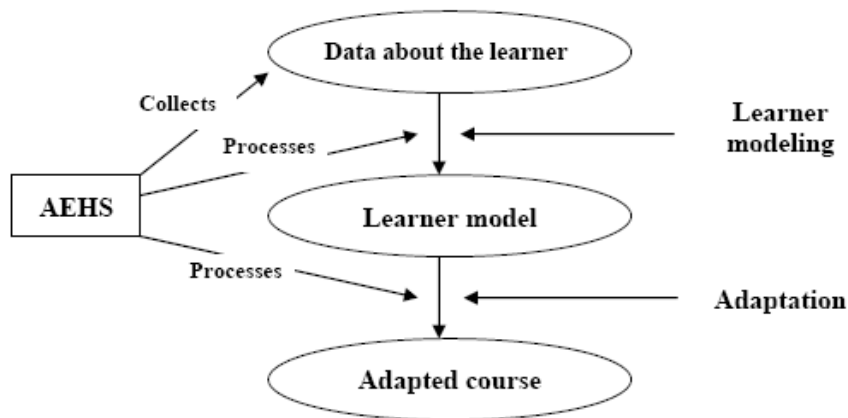


Figure 1.1. Adaptation process in adaptive educational hypermedia systems

The focus of our thesis is on the learning style as the adaptation criterion, since it is one of the individual differences that play an important role in learning, according to educational psychologists. Learning style refers to the individual manner in which a person approaches a learning task. For example, some learners prefer graphical representations and remember best what they see, others prefer audio materials and remember best what they hear, while others prefer text and remember best what they read. There are students who like to be presented first with the definitions followed by examples, while others prefer abstract concepts to be first illustrated by a concrete, practical example. Similarly, some students learn easier when confronted with hands-on experiences, while others prefer traditional lectures and need time to think things through. Some students prefer to work in groups, others learn better alone. These are just a few examples of the many different preferences related to perception modality, processing and organizing information, reasoning, social aspects etc, all of which can be included in the learning style concept.

Research in this area began relatively recently and only a few systems that attempt to adapt to learning styles have been developed. Consequently, "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 and Rodriguez, 2004). However scientists agree that taking these student characteristics into account can lead to an increased learning performance, greater enjoyment, enhanced motivation and reduced learning time (Kelley and Tangney, 2006). We therefore believe that accommodating learning styles in adaptive educational hypermedia is a worthwhile endeavor and this is why we chose it as the theme of our thesis.

The subject requires an interdisciplinary approach, as (Papanikolaou and Grigoriadou, 2004) noted: "Important decisions underlying the incorporation of learning style characteristics in AEHS demand the synergy of computer science and instructional science, such as: (i) the selection of appropriate categorizations, which are appropriate for the task of adaptation, (ii) the design of adaptation, including the selection of appropriate adaptation technologies for different learning style categorizations and of appropriate techniques for their implementation, (iii) the design of the knowledge representation of such a system in terms of the domain and the learner model, (iv) the development of intelligent techniques for the dynamic adaptation of the system and the diagnosis process of learners' learning style including also the selection of specific measurements of learners' observable behavior, which are considered indicative of learners' learning style and studying attitude." More specifically, the research issues that we tried to address throughout this paper are summarized in the next section.

1.2. Research Questions

The following research issues were investigated in this thesis:

1. What learning style model is most appropriate for use in AEHS and how can learning style be diagnosed?

The first step towards providing adaptivity is selecting a good taxonomy of learning styles. Most of the educational systems developed so far rely on a single learning style model, such as those proposed by (Felder and Silverman, 1988), (Honey and Mumford, 2000), (Biggs, 1987) or (Witkin, 1962). We advocate the use of a unifying learning style model, which integrates characteristics from several models proposed in the literature.

The traditional method for diagnosing learning style implies having the students fill in a dedicated psychological questionnaire. What we propose in this thesis is an implicit modeling method, which is based on the analysis and interpretation of student behavior in the system.

Furthermore we address questions such as: What learning style characteristics should be diagnosed and adapted to? How can we create a quantitative model of complex

psychological constructs? What type of information is needed from students' behavior to identify their learning preferences?

2. How can an AEHS perform adaptation according to different learning styles?

The amount of information made available in current e-learning systems is very large, definitely larger than what could be presented by traditional teaching means. While being a positive aspect, this availability can also have a downside - it could easily become overwhelming for the students. It is therefore of a particular importance to filter the content in order to avoid cognitive overload of the learners. Furthermore, it is important to decide how to best present this content and in what sequence (the navigation type).

Within this thesis we try to identify the adaptation technologies that best serve learners with different learning styles and define the corresponding adaptation rules.

3. How can we build a learning style based adaptive educational system and how efficient is it?

Based on the methods and techniques proposed for modeling and adaptation, we designed and implemented such an e-learning platform, called WELSA (**W**eb-based **E**ducational system with **L**earning **S**tyl **A**daptation), which includes several functionalities:

- a course player for the students, enhanced with learner tracking capabilities and an adaptation component
- an analysis tool, used for identifying students' learning preferences
- a course editor for the teachers, to help them author courses in the required format.

We had to answer several questions, such as: what is the best way of representing domain, learner and adaptation model? What is the relationship between individual differences and the adaptive features of the system? What criteria are needed for evaluating the resulted system?

Regarding the validity and effectiveness of our system, we used the empirical evaluation approach, by performing several experiments with undergraduate students. Empirical studies are of a particular importance in the field of adaptive systems, as outlined by (Weibelzahl, 2005). We employed a layered evaluation framework (Brusilovsky et al., 2004), assessing the two processes individually: first the learner modeling phase (which is considered successful if the created student model accurately reflects the student's characteristics) and second the adaptation decision making (which is considered successful if the applied adaptation techniques improve students' performance and/or enjoyment). Finally, the system was evaluated globally, from the point of view of learner motivation, efficiency, effectiveness and overall satisfaction.

Brown et al. (2006) launched a doubt casting question: "just because we *can* use learning styles in adaptive web based educational systems, does this mean that we *should*?" We will prove throughout this thesis that the answer is a definite "yes".

1.3. Thesis Outline

This thesis is organized in seven chapters.

In chapter 1 we discussed the motivation and problem statement of the thesis, outlining the research issues that will be investigated.

Chapter 2 gives an overview of the state-of-the-art in adaptive educational hypermedia systems. Several aspects are covered, including adaptive hypermedia and adaptation engineering, adaptivity in e-learning, learner modeling, adaptation levels, technologies and models, evaluation methodology. Some examples of adaptive educational hypermedia systems are also included.

Chapter 3 introduces the concept of learning styles, as well as their implications for pedagogy. Issues regarding the incorporation of learning styles in AEHS are discussed and the criticism related to learning styles is addressed. An answer to the first part of the research question 1 is provided, by introducing and motivating the use of a "unified learning style model". Parts of this chapter were published in (Popescu, 2006; Popescu et al., 2007a; 2008g).

Chapter 4 deals with the first stage of the adaptation process: the learner modeling, answering the second part of the research question 1. First the student behavior in an AEHS is investigated and relevant patterns of behavior are identified. Two experimental studies are performed, which reveal significant differences between the interaction patterns of students with different learning styles. Based on these findings and on literature review, a method for automatic identification of student learning style is proposed. The approach is validated by means of an empirical evaluation, involving 75 undergraduate students. Parts of this chapter were published in (Popescu, 2007a; 2007b; 2008b; Popescu et al., 2008b; 2008c).

Chapter 5 focuses on the adaptation decision making stage and answers the second research question. Adaptation strategies and techniques are proposed for each of the student learning preferences identified in the previous chapter. The adaptation logic is formalized as modularized sets of rules. The effectiveness of the adaptation process is confirmed by means of an experimental study: the results obtained (student behavior, performance, efficiency and satisfaction) are discussed and analyzed. Parts of this chapter were published in (Popescu, 2007c; Popescu et al., 2006; 2007b; 2007c; 2007d; 2007e).

Chapter 6 addresses the third research question, by presenting the dedicated WELSA learning style based adaptive educational system. Various aspects are covered, related to system architecture, intelligent way of organizing the learning material,

functionalities, technologies, design and implementation. Each of the system components are presented (course player, adaptation component, modeling tool, course editor tool). The experimental validation of the system is done by creating and implementing a course module in the area of Artificial Intelligence and testing it with the students. Parts of this chapter were published in (Popescu, 2008a; Popescu et al., 2008a; 2008d; 2008e; 2008f).

Finally, chapter 7 concludes the thesis, giving a summary of its main contributions, discussing its limitations and pointing towards future research directions.

Chapter 2

Adaptive Educational Hypermedia Systems

Adaptive hypermedia systems for e-learning represent a continuously growing research domain, involving knowledge from several fields (adaptive systems, adaptive hypermedia, learning management systems, user modeling, educational psychology, instructional science). This chapter deals mainly with the technical aspects of adaptive educational hypermedia systems, while the educational aspects are tackled in the next chapter.

The first section presents an overview of adaptive hypermedia in general, as well as adaptation engineering approaches. Next, background information on adaptivity in e-learning is provided. Section 2.3 is devoted to the first stage of the adaptation process: the building and updating of the learner model. The adaptation provisioning stage is reviewed in section 2.4, including adaptation levels and technologies, adaptation models and ways of representing adaptation knowledge. Once the adaptive system is built, an important part is its testing and validation, therefore section 2.5 is dedicated to the evaluation approaches. The chapter ends with some examples of adaptive educational systems, which are provided in section 2.6.

2.1. Adaptive Hypermedia Overview

Hypermedia is an extension of the term multimedia (which includes a variety of presentation supports: text, graphics, audio, video) which provides a non-linear access to information. The term was first coined by Theodor Nelson in 1965, the scientist who also introduced the term "hypertext" (Nelson, 1965). The World Wide Web is a classic example of hypermedia. The first hypermedia system was the Aspen Movie Map, developed at MIT by Andrew Lippman in 1978. It allowed the user to take a virtual tour through the city of Aspen, Colorado. This was accomplished with the use of four video cameras, which were pointed in different directions and took video footage while mounted on the back of a truck through the streets of Aspen. Once the footage was recorded, the pictures were linked together and allowed the user to choose one of several predefined paths in which to tour the city. Using videodisc technology, the Aspen Movie Map allowed for non-sequential access to the program's data and allowed the user to start at a particular point and move forward, back, left, or right. The Aspen Movie Map also contained footage of the inside of notable landmark buildings in Aspen, allowing the user to take a virtual tour through those buildings. Another notable feature of the system was a navigation map which allowed the user to jump directly to a point on the Aspen city map

instead of finding the way through the city streets to that destination. It is because of this feature that the Aspen Movie Map is thought to be the first hypermedia system (Lippman, 1980).

Adaptive hypermedia systems (AHS) are a relatively new research direction, situated at the intersection of hypermedia and user modeling (Brusilovsky, 2001), offering an alternative to the traditional "one-size-fits-all" approach. Adaptive hypermedia systems store a user model (goals, preferences, knowledge level) that they use during the interaction with the user in order to adapt to her/his needs.

Adaptation can take 3 forms (Edmonds, 1981):

- adapted systems – in which adaptation is hard-wired by the application designer; in this case, the system is customized to a particular user profile, which is defined beforehand, at design time.
- adaptable system – in which adaptation is explicitly required by the user. More precisely, the user can specify her/his own preferences, by manually creating her/his profile; thus the system is dealing with a fixed profile, which can only be modified by user's intervention.
- adaptive systems – in which adaptation initiative belongs to the system itself, based on continuous observation of user preferences and needs. The user's profile is no longer static, it is dynamically updated by the system, after tracking and analyzing user behavior.

The research on hypermedia systems has started at the beginning of the 90's; (Brusilovsky, 1996) contains a review of the adaptive hypermedia systems, methods and techniques used in that time. Since 1996, the interest towards adaptive hypermedia systems has grown considerably; the main factors that led to this growing interest are the huge development of the Web and the accumulation of research experience in the domain.

The first "pre-Web" generation of adaptive hypermedia systems mainly explored adaptive navigation and presentation, focusing on the user's knowledge and goals. Empirical studies have shown that adaptive navigation support triggers a higher navigation and learning speed, while adaptive presentation contributes to a better understanding of the content (De Bra et al., 2004). The second "Web" generation explored new technologies based on user interests modeling, as well as dynamic content selection or adaptive recommendations. The third "new adaptive Web" generation is based on modern concepts of "semantic Web" and "mobile Web" (Brusilovsky, 2004), as well as Web 2.0 (O'Reilly, 2005; Sigala, 2008).

Current research in hypermedia systems focuses on the following directions:

- extension of adaptive hypermedia applications beyond traditional approaches: integration with other applications, extension towards open corpus documents (Web), orientation towards mobile devices (PDA, mobile phones etc)

- application of new technologies (natural language generation, non-symbolic AI technologies – machine learning, Bayesian models, neural networks)
- new architectures (component-based architectures integrating user model servers), frameworks that allow automatic generation of adaptive hypermedia systems (shells, authoring tools).

The main application domains for adaptive hypermedia systems are (Brusilovsky, 2001):

- educational hypermedia systems
- on-line information systems (digital encyclopedias, virtual museums, on-line guides, e-commerce systems)
- information retrieval hypermedia systems.

Adaptation Engineering

(Houben et al., 2005) provides a review of existing *adaptation engineering approaches* to date:

- general object-oriented software engineering approaches: Unified Process (Jacobson et al, 1999); however these lack specific hypermedia aspects.
- specific methodologies for hypermedia: RMM (Isakowitz et al, 1998), OOHDM (Schwabe and Rossi, 1998); however these lack aspects related to adaptation
- UML-based Web Engineering approach (Koch, 2001; Knapp et al, 2003); however these lack aspects related to semantics
- Reference models for adaptive hypermedia systems: AHAM (Adaptive Hypermedia Application Model) (De Bra et al., 1999), Munich Model (Koch and Wirsing, 2002), LAOS (Cristea and Mooij, 2003), WebML (Web Modeling Language) (Ceri et al., 2000), XAHM (XML Adaptive Hypermedia Model) (Cannataro et al., 2002)

(Houben et al., 2005) classifies *concept-based systems* into three categories:

- Adaptive Web information systems, which are data intensive applications, making use of data repositories. Hera (Vdovjak et al., 2003) is an example of such a system. Its conceptual model is based on RDF, also defining how the content is retrieved and how the semantic differences between sources are treated. The adaptation module is based on a user profile (content presentation preferences that are fixed) in order to provide adaptability and on a user model (knowledge level that changes according to the navigation progress) in order to provide adaptivity.
- Adaptive hypermedia systems, e.g. AHA!, a system developed starting with 1996, when an on-line course text on the subject of hypermedia was augmented with adaptive content and linking. Since then the software for that course has been changed and extended, which led to AHA! version 1.0 (De Bra et al., 2000). Next the system was extended with event-condition-action rules, concept relationships described through generic rules, a more flexible user model structure allowing multiple concepts, and a

more versatile structure of these concepts with arbitrary attributes. This led to version 2.0. of AHA! system (De Bra et al., 2002). The domain model is represented as concepts with attributes and relationships ("prerequisite", "interest"). The concepts are separate from the actual content; the resources are a fixed set of data elements that are known to the designer. The user model is an overlay model, in which each concept will have several attributes associated to it: "knowledge", "interest", "access", "suitability", "visited". The adaptation model consists of a set of rules, requiring an adaptation engine to execute them. There are two types of rules available: navigation behavior determines changes in the user model and at the same time the user model determines changes in navigation and presentation. In AHA! domain and adaptation models are combined since the adaptation rules are associated to attributes of concepts in the domain model. More recently the system was improved with more efficient ways of handling conditional content, layout capabilities and more extended versions of the authoring tools, which led to AHA! version 3.0 (De Bra et al., 2006). AHA! can be seen as a universal authoring framework for developing AHS, allowing authors to introduce generalized concepts and relationships between concepts. These concepts can represent different user aspects such as knowledge, goals and interest.

- Adaptive task-based systems, e.g. AIMS (Aroyo and Dicheva, 2003). The domain model is based on a concept structure, a meta-layer over the actual content. Unlike AHA!, which starts from given content that is structured by associating concepts to fragments, AIMS starts from concept structures (ontology) and associates content only later, at run-time. The concepts are described by attributes ("name", "synonyms", "description", "context of use", "weight") and links ("is-a", "part-of", "implemented-in", "applied-for"). The data elements are only known at schema level, like in a database application. There is an additional model, the resource library model, in which resources are semantically described using metadata with educational applicability, which also connect the resources with the concepts in the domain model. Thus the adaptation is also realized by means of the association between concepts and resources. Each course topic is seen as a set of tasks; each task has goals, a set of domain concepts, a set of learning activities and a set of pre and post-conditions, used in the adaptation rules. The course task model selects the concepts appropriate for a specific task (from the domain model) and assigns resources to them (from the resource library model) and manages the sequencing of materials. Finally the user model is represented as an overlay model of the domain model. Thus there are three groups of authoring activities: domain-related, course-related and resource-related.

2.2. Adaptivity in E-learning

A conceptual definition of adaptivity in e-learning refers to the creation of educational experiences that adjust based on various conditions (personal characteristics, pedagogical approach, user interactions, learning outcome) during a certain amount of time in order to improve performance indicators (e-learning efficiency: results, time, costs, user satisfaction) (ALFANET, 2005). The functional definition refers first of all to the main characteristics provided by the system. An adaptive system must be capable of managing learning paths adapted to each user, monitoring user activities, interpreting them using specific models, inferring user needs and preferences and exploiting user and domain knowledge to dynamically facilitate the learning process (Boticario et. al, 2005).

(Brusilovsky and Peylo, 2003) identifies three major *development paradigms in AI-Ed* (Artificial Intelligence in Education):

- Intelligent Computer-Assisted Instruction (ICAI) → representative of the 1970s, using classic mainframes and mini-computers as platforms. The main goal of these systems was the transfer of knowledge to the student, therefore the learning material consisted mainly of presentations and also some exercises and problems. Correspondingly, the most popular technologies were curriculum sequencing and intelligent solution analysis (Carbonell, 1970; Brown et al., 1973; Koffman and Perry, 1976; Brown and Burton, 1978).

- Intelligent Tutoring Systems (ITS) → representatives of the 1980-1990s, using personal computers as the support platform. The main goal shifted from educational material presentation to supporting the student in solving problems and procedural knowledge formation. Consequently the core technology became interactive problem solving support.

- Web-based educational (WBE) systems → representatives of late 1990s – 2000s, having the WWW as support platform. The goals of these systems became more complex and diverse, including at the same time content delivery, problem solving support and collaborative work support. Consequently multiple technologies were employed, ranging from adaptive curriculum sequencing, adaptive hypermedia, adaptive information filtering, intelligent solution analysis, intelligent collaborative learning, class monitoring.

Our research is oriented towards the adaptive and intelligent Web-based educational systems (Brusilovsky and Peylo, 2003). Adaptive systems are those systems that try to behave differently toward each student, based on the information accumulated in the student model, while intelligent systems apply artificial intelligence techniques in order to comply with the needs of their users. The majority of educational Web systems belong to both categories; however, there are some exceptions, both intelligent systems that are not adaptive, like German Tutor (Heift and Nicholson, 2001) or SQL-Tutor (Mitrovic, 2003) and adaptive hypermedia systems that use very simple adaptation

techniques, which cannot be called "intelligent", like AHA! (De Bra et al., 2003) or WebCOBALT (Mitsuhara et al., 2002).

(Brusilovsky and Peylo, 2003) identifies the following *technologies in Adaptive and Intelligent Web-Based Educational Systems (AIWBES)*:

- Intelligent Tutoring
 - curriculum sequencing technology → provide the student with an optimal path through the learning material, in the form of recommended links, adaptive "next" buttons as in ELMART (Weber and Brusilovsky, 2001) or suggested learning path as in KBS-Hyperbook (Henze and Nejd, 2001).
 - intelligent solution analysis → analyze the student's solutions to various problems (ranging from simple questions to complex programming assignments), identify the error source and provide appropriate feedback to the students, while at the same time updating the student model. Examples of systems that involve intelligent solution analysis include SQL-Tutor (Mitrovic, 2003), German Tutor (Heift and Nicholson, 2001) and ELM-ART (Weber and Brusilovsky, 2001)
 - interactive problem solving support → provide students with intelligent help during the problem solving process (hints, explanations, partial solutions). Some of the systems that deal with interactive problem solving support are ActiveMath (Melis et al., 2001), AlgeBrain (Alpert et al., 1999) and ELM-ART (Weber and Brusilovsky, 2001).
- Adaptive hypertext and hypermedia systems
 - adaptive presentation technology → adapt the content of each page to student goals and knowledge, by dynamically generating or assembling pages for each student, according to the student model. Examples include ActiveMath (Melis et al., 2001) and MetaLinks (Murray, 2003)
 - adaptive navigation support technology → provide the student with an optimal learning path, but in a more flexible manner than traditional curriculum sequencing. The student is offered guidance through the learning material by means of annotating, sorting or hiding links, but eventually she/he has the final choice regarding the links to follow. This is a very popular technique, used by most of the AIWBES, among which: InterBook (Brusilovsky et al., 1996), ActiveMath (Melis et al., 2001), MLTutor (Smith and Blandford, 2003), AHA! (De Bra et al., 2003).
- Adaptive information filtering → adapt the results of Web search using filtering, ordering and link generation, either based on content or on matching users with similar interests. The technique can also be used in educational contexts, for retrieving learning materials from open corpus educational resources. Adaptive information filtering usually relies on machine learning techniques.

- content-based filtering → MLTutor (Smith and Blandford, 2003)
- collaborative filtering → WebCOBALT (Mitsuhara et al., 2002).
- Intelligent collaborative learning → situated at the intersection between computer supported collaborative learning (CSCL) and ITS.
 - adaptive group formation and peer help → use the characteristics in the student model to form optimal work groups (Greer et al., 1998; Graf and Bekele, 2006) or to find the most appropriate peer to offer help (McCalla, et al., 1997; Inaba et al., 2000)
 - adaptive collaboration support → offer advice to collaborating peers, using knowledge about good and bad collaboration patterns, either provided by the system design or learnt from communication logs. Some examples include COLER (Constantino Gonzalez et al., 2003) and EPSILON (Soller and Lesgold, 2003).
 - virtual students → provide virtual peers as learning companions or troublemakers (Chan and Baskin, 1990; Frasson et al., 1996). A promising direction is the integration of animated agents to support learning and collaboration.
- Intelligent class monitoring → provide teacher support, offering information regarding student feedback; artificial intelligence techniques are used to analyze and interpret student behavior. Some systems that offer this functionality are: HyperClassroom (Oda et al., 1998), (Merceron and Yacef, 2003), (Romero et al., 2003).

The focus of our thesis is on *adaptive educational hypermedia systems (AEHS)*. According to (Paule Ruiz et al., 2008), these are systems that "deliver personalized views or versions of hyperdocuments and these systems use a user model and a concept model within the learning environment to decide what content and type of navigation to present, as well as how to best present these contents."

There are three factors that must be taken into account when talking about adaptation in e-learning systems:

- the student (who is characterized by her/his knowledge level, technical background, learning goals, interests, motivation, cultural background, learning styles, personality traits etc)
- the hardware and software platform (PC/laptop/PDA/mobile phone etc, screen size, available input devices, connection bandwidth, processor performance, memory size, operating system, web browser etc)
- the environment (the physical environment where interaction takes place - surrounding light, noise, geographical location and other external elements that may have an influence).

According to (ALFANET, 2002), adaptation can have several dimensions:

- number of criteria taken into account (single versus multiple criteria)
- the moment of student data collection (pre-assessment versus tracking)

- the locus of control (system-centered versus learner-centered).

The adaptation process in an educational system consists of two stages: first, a model of the learner must be created and second, based on the traits contained in this model, an individualized educational experience is provided. An overview of the former stage is included in the next section, while the latter stage is succinctly surveyed in section 2.4.

2.3. Learner Modeling in AEHS

A distinct feature of an adaptive system is the user model it employs, i.e. a representation of information about an individual user. User modeling is the process of creating and maintaining an up-to-date user model, by collecting data from various sources, that may include implicitly observing user interaction and explicitly requesting direct input from the user (Brusilovsky and Millan, 2007). User modeling and adaptation are strongly correlated, in the sense that the amount and nature of the information represented in the user model depend largely on the kind of adaptation effect that the system has to deliver.

Brusilovsky and Millan (2007) analyze user models in adaptive hypermedia and adaptive education systems, from three points of view: nature and information (what is being modeled), structure and representation (how the information is represented) and user modeling approach (how the model is constructed and maintained). Regarding the information contained in the user model, there are identified six features: knowledge, interests, goals, background, individual traits and context of work. The first five represent the user as an individual and are important to all adaptive Web systems, while the latter is mostly of interest to the mobile and ubiquitous adaptive systems (see Fig. 2.1.)

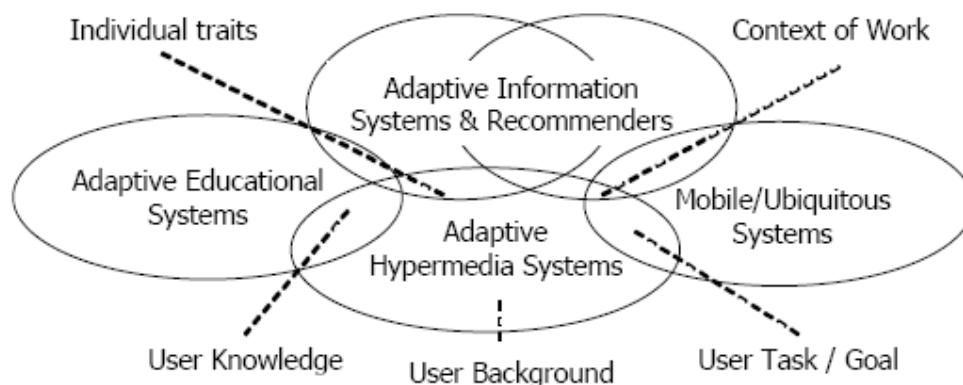


Figure 2.1. User features typically modeled by different classes of adaptive Web systems (Brusilovsky and Millan, 2007)

The *learner's knowledge* of the subject being taught is the most widely used student feature being modeled in an AEHS. There are several types of knowledge models:

- scalar model, which estimates the student knowledge level by means of a grade on a given scale, either quantitative (e.g. a number ranging from 0 to 10) or qualitative (e.g. good, average, poor). Despite their simplicity, scalar models were widely and effectively used to support adaptation.
- overlay model, which estimates the student knowledge level as a subset of the domain knowledge. The information included in the pure overlay model indicates whether the student knows or not a domain fragment (yes or no value). The information in modern overlay models indicate the degree to which the learner knows the respective fragment - either a qualitative measure (e.g. good – average – poor) or a quantitative measure (e.g. the probability that the student knows the concept). The represented knowledge can be of two types: conceptual (facts and relationships) or procedural (problem-solving skills). The first is usually represented by a network of concepts, while the latter is represented as a set of problem solving rules.
- bug model, which is an overlay model extended so as to represent both correct knowledge and misconceptions. The perturbation model is a widely used version of bug model, in which it is assumed that incorrect user behavior is caused by the systematic application of a perturbation instead of the correct rule.
- genetic model, which is the richest model, that aims at reflecting the process of knowledge genesis in the student mind, from simple to complex and from specific to general.

The most widely used is the overlay model, which provides a good balance of simplicity and power.

User interests were usually neglected in AEHS, being largely addressed in the information-oriented AHS, such as encyclopedias, news systems, electronic stores, museum guides, where access to information is mostly interest-driven. However, more recently learner interests have started to be modeled also in AEHS, due to the advent of the interest-driven constructionist approach to education.

The *learning goal of the student* is her/his most changeable trait, varying from session to session and even during one course session. The learner's goal is usually modeled using a goal catalog approach, which includes the possible goals that the system can recognize. The catalog can contain either independent goals or a goal hierarchy, with longer term goals at the higher levels and shorter term goals at the lower levels of the hierarchy.

The *learner's background* refers to her/his previous experience outside the core domain of the educational system (e.g. the technical background, learner's experience with web-based educational systems). The difference between learner's knowledge and learner background is in its representation (overlay model in the first case and a simple stereotype model in the second) and in the construction method – the learner's

background is usually provided explicitly, since it is difficult to be inferred from the student interaction with the system.

The *learner's individual traits* refer to personality traits, cognitive styles, cognitive factors and learning styles. They are usually identified by means of specially-designed psychological questionnaires. The focus of this thesis is on the latter category of learner traits, which will be detailed in the next chapter.

The *context of the user's work* is a relatively new research direction in AHS and refers to: i) the user platform: hardware, software, network bandwidth (e.g. screen size, media presentation capabilities etc); ii) user location; iii) environment dimension - spatio-temporal aspect and physical conditions (light, temperature, acceleration, pressure, etc.); iv) human dimension: personal context (user pulse, blood pressure, mood, cognitive load), social context, and user task; v) affective state (motivation, frustration, engagement, disengagement).

There are two possible approaches to learner modeling:

- feature-based modeling, which considers specific features of individual users, as discussed above (knowledge, interests, goals etc).
- stereotype-based modeling, in which learners are clustered in several groups, and the adaptation is then performed based on the belonging to one of these groups. Each stereotype corresponds to a combination of features and each student is assigned to one stereotype based on her specific combination of traits. Once a student is categorized, the system will be customized based on the category which has been set for the student.

Brusilovsky (1994) identified several methods for constructing and updating student models:

- implicit methods – based on tracking student actions during a problem solving process
- explicit methods – based on the direct dialogue between the system and the student (questionnaires, evaluation tests etc)
- structural methods – based on the structure of the knowledge interrelations (possessing one element of knowledge conditions the acquirement of others; possession of a more complex ability implies possession of a simpler one etc)
- historic methods – based on the estimate of the initial knowledge level and past experience.

Kobsa et al. (2001) distinguished three categories of user related data:

- user data, which refers to information about individual characteristics of the user, as discussed above (knowledge, interests, goals, background, learning style)
- usage data which is related to information on the user's interactive behavior: selective actions (e.g. clicking on a link, scrolling and enlarging operations for hypermedia objects, audio control operations), temporal viewing behavior, rating (users are required to explicitly rate objects, links, web pages). Some of these interactions can be used directly in the adaptation process, while others require some pre-processing,

resulting in information such as usage frequency, action sequences and situation-action correlations.

- environment data which comprises aspects of the user environment such as spatio-temporal location of the user and the user platform (broadly corresponding to the context of work described above).

The methods used for interpreting these data and constructing student models can be classified in three categories: formal, semi-formal (heuristic) and informal (ad-hoc) (Yudelson et al., 2005). ELM-ART (Weber and Brusilovsky, 2001) is an example of system that uses ad-hoc approach. Formal approaches use methods either from cognitive sciences (Anderson et al., 2004), or from artificial intelligence (semantic networks, rule-based reasoning, machine learning, neural networks, genetic algorithms, Bayesian networks).

A user modeling problem can be defined as follows, according to (Muller, 2005): a learning algorithm A induces a user model M_u based on background knowledge and feedback f , which is recorded by collecting and interpreting observable interactions.

However there are a set of users' characteristics that must be taken into account in the machine learning process:

- users are not willing to give feedback, therefore there are only few examples available for the learning algorithm
- users need to be observed unobtrusively, consequently the samples are noisy and not reliable
- users need to feel in charge, so the system behavior must be explained to the user
- users must be motivated to spend extra effort, so the learning must be fast and failsafe.

Also it must be taken into account the fact that what is actually being modeled is not the user's interest but her/his behavior (which is an indicator of user's interest but not equivalent to it). Thus learning is based not on observables, but on interpretations of observables.

Regarding the use of the learner model, (Brusilovsky, 1994) identified several methods and techniques:

- knowledge development, with three stages: i) Precisely identify the missing knowledge element (what to teach?): goal-oriented tutoring versus active help versus passive help; ii) Choose the adequate moment for knowledge development (when to teach?): right at the moment of the mistake versus accumulate errors in the student profile and give explanations at the most appropriate time; iii) Choose the adequate method for knowledge development (how to teach?): explanations, tests, examples, problems.
- error remediation, with 8 possible methods: error definition, explicit remediation, implicit remediation or prompting, counter examples, demonstration of a solution method, access to previous experience, repeated attempt, tactical retreat.

- knowledge diagnostics
- strategic functions (plan modifications in case the current strategy doesn't work for a particular student)
 - prediction of student behavior and student learning path
 - assessment of the student
 - assessment of the system.

Once the learner model is created, it can be used for adaptation provisioning, which is the subject of the next section.

2.4. Adaptation Provisioning

In what follows we will present the adaptation component, briefly reviewing the adaptation levels and technologies, adaptation models and ways of representing adaptation knowledge.

2.4.1. Adaptation Levels and Technologies

A *method* is defined as a notion of adaptation that can be presented at the conceptual level. A *technique* is a way to implement a specific method. Techniques operate on actual information content and on the presentation of hypertext links. It may be possible to implement the same method through different techniques and to use the same technique for different methods (Stash, 2007).

Brusilovsky wrote several reviews regarding the methods and techniques for adaptive hypermedia (Brusilovsky, 1996; 1997; 1998; 2001; 2004; 2007). Some of them deal only with adaptive navigation support (Brusilovsky, 1997; 2004; 2007) while the others deal with other aspects also (such as classification of AH systems, adaptive presentation methods and techniques, user modeling in AHS etc). According to the most recent classification (Brusilovsky, 2001), he distinguishes two levels of adaptation:

- content level adaptation or adaptive presentation
- link level adaptation or adaptive navigation support.

Indeed, by abstracting hypermedia as a graph, we can either adapt its nodes (content level adaptation) or its edges (navigation level adaptation).

Figure 2.2 provides a summary of the adaptive hypermedia technologies (Brusilovsky, 2001), while Table 2.1 illustrates the applicability of various adaptive navigation support technologies.

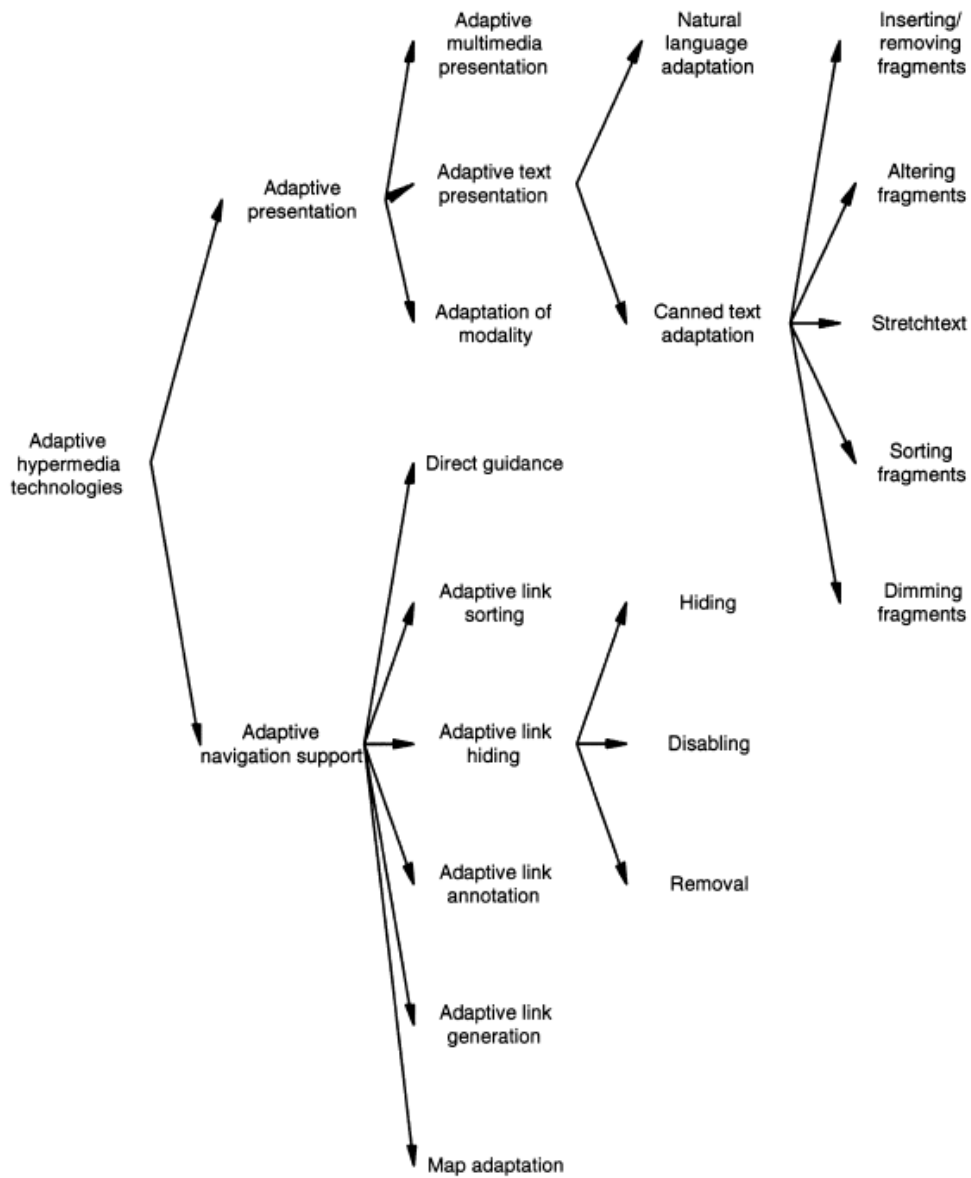


Figure 2.2. Taxonomy of adaptive hypermedia technologies - according to (Brusilovsky, 2001)

	Direct guidance	Sorting	Hiding	Annotation	Generation
Contextual links	OK		Disabling	OK	
Non-contextual links	OK	OK	OK	OK	OK
Table of contents	OK			OK	
Index	OK			OK	
Hyperspace maps	OK		OK	OK	

Table 2.1. Adaptive navigation support technologies and their applicability (Brusilovsky, 2007)

For the more general case of adaptive educational systems (AES), (ALFANET, 2005) identifies another level of adaptation, namely:

- Collaboration Level Adaptation – the system can help to form the most appropriate workgroups taking into account student collaboration profile; it can also provide a student with information regarding other students involved in the same activity or project and also guide the student toward the most appropriate peer to offer support in a particular problem.

(Dolog et al., 2007) mentions examples of adaptive navigation support, adaptive content presentation, adaptation of pedagogical strategies and adaptation of complete learning environments. According to (Dolog et al., 2007), adaptation strategies can be classified into three basic categories: adaptive selection of media items, adaptive ordering of media items and adaptive tools for navigation support. The selection can be based not only on different media types (such as text, image, video, audio presenting the same concept) but also on other criteria such as instructional role (definition, example, algorithm etc). The same criteria can be applied for the ordering of items. Finally, as far as the tools for navigation support are concerned, learners can be provided with concept maps, graphic path indicators or advanced organizers.

(Kravcik and Gasevic, 2007) identifies also other adaptation dimensions such as:

- adaptive learning activity selection
- adaptive recommendation
- adaptive service provision.

Thus adaptation can be done at:

- process layer (selection, design, structure)
- material layer (selection, design, structure, presentation)
- adaptation layer (selection of adaptation strategies, i.e. meta-adaptation).

Regarding the last layer, there are several studies (Brusilovsky, 2003; Brusilovsky et. al, 2004) which suggest that the student knowledge level as well as her/his previous experience with hypermedia systems may have an influence on the effect of the adaptation technique used. For example students with higher previous knowledge prefer non-restrictive adaptive methods that provide additional information (adaptive annotation, multiple link generation), while students with low 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.

2.4.2. Adaptation Models

There are several attempts to model adaptive hypermedia - Adaptive Hypermedia Application Model (AHAM) is a reference one (Wu et al., 2001). AHAM provides a framework to express the functionality of adaptive hypermedia systems by dividing the storage layer into three parts that specify *what* should be adapted, *according to what* features it should be adapted, and *how* it should be adapted (see Fig. 2.3):

- a domain model – which is represented as concept maps, semantic networks, concept graphs or ontologies
- a user model – which is usually represented as an overlay model of the domain model in order to describe the knowledge level of the user; additionally, user's cognitive or presentation preferences can be recorded
- an adaptation model – the specification of adaptation rules (the adaptive methods and techniques used for content selection, navigation or presentation).

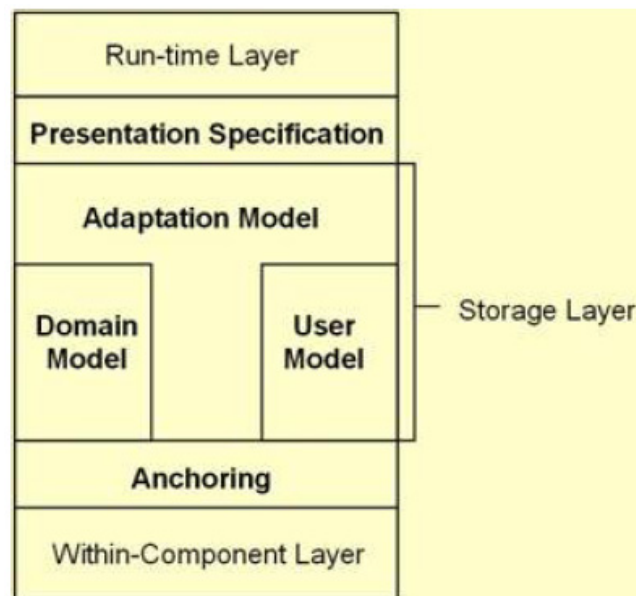


Figure 2.3. Adaptive Hypermedia Application Model (De Bra et al., 1999; Wu et al., 2001)

(Kravcik and Gasevic, 2007) suggests the addition of two more layers: context model (current environment and settings) and activity model (the learning design) (see Fig. 2.4). The activity and adaptation models represent the procedural knowledge of the adaptive application, while the other models represent the declarative knowledge.

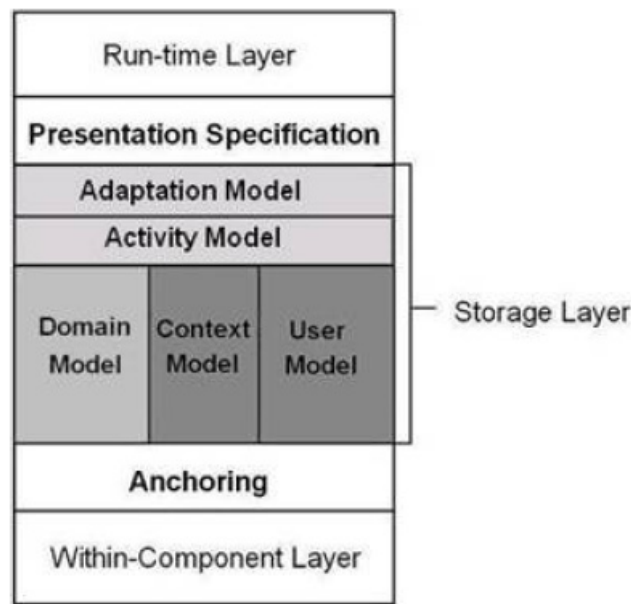


Figure 2.4. Enhanced Adaptive Hypermedia Application Model
(Kravcik and Gasevic, 2007)

LAOS (Cristea and De Mooij, 2003) is a generalized model for generic adaptive hypermedia authoring, based on the AHAM model and on concept maps. LAOS includes the following components (see Fig 2.5):

- domain model (DM)
- goal and constraints model (GM)
- user model (UM)
- adaptation model (AM)
- presentation model (PM)

In order to provide reusability, better semantics and standardization, Cristea and Calvi (2003) introduced LAG, a generalized adaptation model for generic adaptive hypermedia authoring. LAG contains 3 components, with different levels of granularity:

- Direct Adaptation Techniques → adaptation assembly language
- Adaptation Language → adaptation programming language
- Adaptation Strategies → adaptation function calls

According to (Stash et al., 2005), actions in these adaptation strategies can be classified in several categories:

- Basic actions on items
 - Selection
 - Showing the content of an item
 - Showing a link to an item
- Hierarchical actions on items
 - Actions on child items

- Actions on parent items
- Actions on groups of items (e.g. siblings)
 - Ordering
 - Performing "actions on items" on each group item
- Actions on the overall environment
 - Changing the layout of the presentation

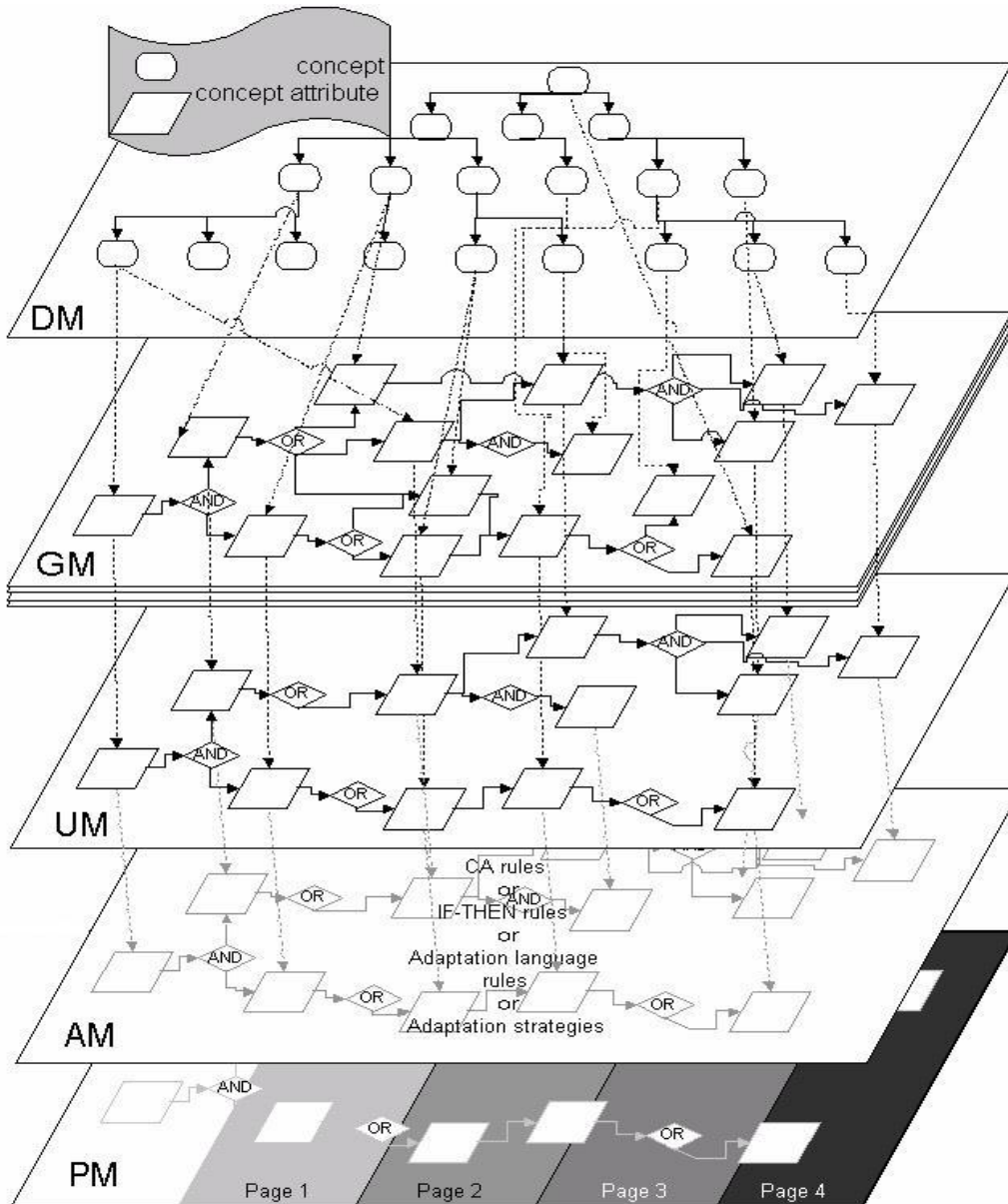


Figure 2.5. The LAOS model (Cristea and De Mooij, 2003)

2.4.3. Representation of Adaptation Knowledge

(Kravcik and Gasevic, 2007) identifies several ways of addressing the issue of procedural knowledge:

- Informal scripts – instructional designers sketch informal scripts to describe the design logic and messages for the learner and programmers subsequently implement these ideas. Most of the knowledge is incorporated implicitly in the design scripts, and hence not reusable. Example: (Bork, 2001)
- System encoding – the procedural knowledge is encoded in the system, so all the courses created in that system can reuse it. Authors only have to specify the declarative knowledge (in the form of metadata) and the system generates the adaptive course. However, the procedural knowledge is fixed and the authors cannot include their own adaptation strategies. Example: WINDS project (Kravcik and Specht, 2004)
- Elicited knowledge – the author should be able to specify the learning design and adaptation strategies, in an independent specification from the concrete learning material and contexts. Examples: LAG method (Cristea and Calvi, 2003), FOSP method (Kravcik, 2004).
- Standards and specifications – the most relevant are IMS Simple Sequencing (which only takes into account the learner's current context but no individual differences between learners) and IMS Learning Design (which allows the definition of different learning paths for different users) (IMS Global Learning Consortium, 2008). However, Towle and Halm (2005) claim that IMS LD provides a way to implement simple adaptive learning strategies, but not complex forms of adaptive learning, like multiple rules interactions or enforced ordering (e.g. it is not possible to annotate learning content or define student roles considering their characteristics - (Berlanga and Garcia, 2005))
- Ontologies – the various types of knowledge relevant for adaptive learning could be represented using ontologies. There are several authors that propose the use of ontologies, such as Cristea (2004) (appropriate ontologies for each layer of the LAOS model, namely: domain, goal and constraint, user, adaptation, and presentation ontologies), Henze et al. (2004) (domain ontology, user ontology, observation (interaction) ontology and presentation ontology), or Jovanovic et al. (2006) (content structure ontology, content type (pedagogical role) ontology, learning path ontology, domain ontology, and user model ontology).

2.5. Evaluation Methodology

Weibelzahl (2005) underlies the importance of empirical tests and evaluation in case of adaptive systems.

The most widely used evaluation approach of an adaptive system is to compare it with a non-adaptive version of the system (with the adaptation mechanism turned off). The evaluation can be done in respect to three factors:

- subjective student satisfaction
- learning speed (efficiency)
- assessment results (effectiveness)

Thus the criteria that can be used in the evaluation are: learners' scores in knowledge tests, the time learners spent on the course, the number of their page requests, the number of returns to the same page (getting lost feeling), the eagerness to work with the system etc.

A good evaluation practice is to conduct both formative and summative evaluations and use several smaller experiments rather than a large one. The chosen sample must be heterogeneous in terms of the modeled characteristics but homogeneous in terms of other aspects (e.g. students who differ in reading speed could influence the results). Also empirical results should be reported in a proper way, to allow comparisons with similar studies in the literature.

The traditional "with or without" approach can only evaluate the system as a whole. Thus it presents the following disadvantages (Brusilovsky et al, 2004):

- evaluation can only take place after the whole system is developed
- the evaluation does not clearly identify where the problem is
- successful design practices are not identified so they cannot be easily reused

Therefore a layered evaluation framework is proposed, involving two distinct processes or phases: user modeling and adaptation decision making. These processes are strongly interconnected, since adaptation decision making is based on the results provided by the user modeling component; however they can also be seen as independent, since for the same user model the system may use different adaptation logics. Therefore the two components can be evaluated separately, possibly using different techniques.

Thus the user modeling phase is considered successful if the created student model accurately reflects the student's characteristics. This can be evaluated by comparing the modeling component results with student's answers to dedicated questionnaires, with an educational psychology expert opinion and/or with the student's self-evaluation.

The second phase is considered successful if the applied navigation techniques prove to be efficient for a given state of the student, improving his performance and/or satisfaction. The evaluation of the adaptation decision making process can be done by

starting from a given student model that is considered accurate (created by directly testing the user in order to assess her/his knowledge level or learning style).

Obviously, using this 2-layer approach, various student modeling components (based on different modeling techniques) can be combined with various adaptation decision making components (based on different adaptations logics).

A newer proposal (Paramythis & Weibelzahl, 2005) suggests a 5-layer evaluation approach involving:

- collection of data
- interpretation of data
- modeling of the current state of the world
- deciding about adaptation
- applying adaptation

On the other hand, it can be argued that a successful adaptation does not necessarily imply acceptability from the part of the user (Brusilovsky et al, 2004). The main reason is that adaptive applications can make the user feel he lost control of the application. This is why adaptive systems should be able to justify their decisions and also give the user access to directly modify their profile, if desired. Moreover, the privacy and security of the information stored for the user must be carefully considered, or the user might lose her trust in the application. Thus adaptation should not be seen as a goal in itself, but a way of improving the effectiveness of the system. In this respect, assessing student satisfaction by means of questionnaires is a very important step in the evaluation of an adaptive educational platform.

Finally it should be taken into account the degree of influence of each factor in the learning process: obviously, reinforcement, student's prior cognitive ability, student's disposition to learn, and the instructional quality have bigger influence on the effectiveness of learning than the individualization of instruction to conform to student's learning style. Therefore the obtained data should be carefully analyzed and interpreted.

2.6. Examples of Adaptive Educational Systems

There are several examples of *adaptive educational systems* to date:

- InterBook (Brusilovsky et al, 1998) is the de facto standard in the field of adaptive hypermedia. It is a tool for authoring and delivering *adaptive electronic textbooks* on the Web. InterBook uses the adaptive annotations technique, choosing different icons for links with different status: red bullets for not recommended pages (pages that need more knowledge to be acquired by the student in order to be understood), green bullets for recommended pages and white bullets for pages with no new concepts (traffic light metaphor). Furthermore, links to glossary pages are annotated with checkmarks of different sizes, representing the system's estimate of student's

knowledge of the concept. The user modeling and adaptation decision making processes are reasonably independent. The interface between them is the student model, represented as a vector that records the status of each concept and each book page. This model is dynamically created by observing the student browsing activity: the average time spent on a page is an indicator of the page difficulty for the student.

- KBS Hyperbook (Henze and Nejd, 1998; 1999) is a tool for modeling, organizing and maintaining adaptive, open hypermedia systems on the Web. The implemented hyperbook is used for an introductory course to Java programming. The system implements the following adaptation components: i) *adaptive information resources* (give the students appropriate information while performing their projects, by annotating necessary project resources depending on current student knowledge); ii) *adaptive navigational structure* (adapt/annotate the navigational structure in order to give the student additional information about appropriate material to explore/learn next); iii) *adaptive trail generation* (provide guidance by generating a sequential trail through part of the hyperbook depending on student goals); iv) *adaptive project selection* (provide suitable projects depending on student goals and previous knowledge); v) *adaptive goal selection* (suggest suitable learning goals depending on user's knowledge). KBS Hyperbook does not take into account information about the visited pages or users' paths through hypertext, but it directly asks the user for feedback on different topics after each project unit.

- WebDL (Boticario et al., 2000) offers adaptive navigation support by means of link annotations; it is a multi-agent architecture designed to personalize and adapt various sources of information and communication channels available on the Web.

- ELM ART (Weber and Brusilovsky, 2001) is a web-based introductory LISP course, which supports example-based programming. Adaptivity takes the form of visual annotation of links and program code diagnosis, which is provided as a sequence of help messages adapted to the knowledge level of the student.

- Knowledge Sea (Brusilovsky and Rizzo, 2002) provides access to several online tutorials on the C language, as part of a programming course. It uses content based information retrieval technologies, specifically Self-Organized Maps, a neural network-based mechanism to process a large number of pages from different Web-based tutorials along with a set of closed corpus documents (such as lecture notes) and group them by similarity. It thus provides a map-based horizontal navigation between open and closed corpus items. As a result, a user with a specific educational goal - such as to do readings associated with a particular lecture - can use an automatically generated list of relevant links to explore. Knowledge Sea II system (Brusilovsky and Chavan, 2003) coupled with AnnotatED social navigation system explores some simple forms of social navigation based on group user modeling and the idea of "footprints" (Wexelblat and Mayes, 1997). Each tutorial is annotated with a blue icon on a blue background, representing the number of accesses of the current student (the shade of blue of the icon) and of his peers (the

shade of blue of the background). The color difference between the icon and the background visualizes the discrepancy between user and class navigation patterns.

- KOD (knowledge-on-demand) (Sampson et al., 2002) – is an adaptive e-learning environment which offers personalized content. The system is based on IMS CP (Content Package) standard (IMS Global Learning Consortium, 2008), proposing an extension of it (called Knowledge Packaging Format – KPF), so that it includes an adaptation logic. KPF thus includes adaptation rules which determine what educational resources will be selected and presented to each student, according to her/his profile.

- TASKi (ADAPTIT, 2003) is a generic system that can be used to optimize the process of learning complex cognitive skills in various domains. It is based on a particular pedagogical model, namely 4C/ID (Four Component Instructional Design Model).

- APeLS (Dagger et al., 2003) is based on the three main models: *learner*, *content* and *narrative* (pedagogical) models, which correspond to user, domain and adaptation models of the AHAM model. The learner model uses the stereotype approach and is based on student feedback (learner's answers to questionnaires). The content model is based on a "candidate content group" (CCG), which includes learning resources that are equivalent on some axis (e.g. concept taught, prerequisites or learning style). The *narrative model* captures the logic behind the selection and delivery of a learning resource, allowing the separation of the adaptation and the actual content. APeLS provides adaptive presentation by means of the candidate selectors (the rules that choose a candidate from a CCG) and adaptive navigation by means of the sequencing of candidates in the narrative.

- ALFANET (ALFANET, 2005) also provides an adaptive e-learning platform, focusing on four types of adaptation: course entry point adapted to the level of knowledge based on pre-assessments, course content adapted to learner's style, assessments adapted based on scores of self-tests and recommendations adapted based on learner's style and behavior of similar learners.

More examples of adaptive web-based educational systems include: PLS (Conlan et al., 2002), KnowledgeTree (Brusilovsky and Nijhaven, 2002), INSPIRE (Papanikolaou et al., 2003), AHA! (De Bra et al., 2006), SEDHI (da Silva and Rosatelli, 2006).

The AEHS that we presented in this section differ in several important aspects: approach to learner modeling, technologies for building the learner model, representation of the domain model, methods of defining adaptation etc. However, they all share a common aspect: the main learner feature that drives adaptation is her/his knowledge level, while other features are secondary, if present at all. Our choice to overview this category of AEHS is based on the fact that they are the most numerous and most representative in the AEH field. In the next chapter we will also include the relatively new direction in AEH: learning style based adaptive educational systems (LSAES).

Chapter 3

Learning Styles in Adaptive Educational Systems

Accommodating learning styles in adaptive educational systems is an important step towards providing individualized instruction, since they have a significant influence on the learning process. Attempting to represent knowledge regarding complex psychological characteristics of the learner and adapting the course so as to best suit them is a challenging research goal. We have therefore devoted this chapter to an overview of learning styles. We start with some theoretical aspects, including definitions and examples of learning style models, as well as their implications for pedagogy. Next, in section 3.2 we discuss the application of learning styles in AEHS. First we address the specificities of learning style based adaptive educational systems (LSAES) and then we provide some examples of the most representative LSAES to date.

Section 3.3 addresses the criticism of learning styles. As a response to these challenges we introduce our own approach, which implies the use of a unified learning style model (ULSM), incorporating characteristics from several traditional models. We argue that ULSM is the best choice for a learning style based adaptive educational system and we outline its advantages. A part of the first research question is thus addressed, namely: "What learning style model is most appropriate for use in AEHS?"

3.1. Theory of Learning Styles

3.1.1. Definitions

Learning style is one of the individual differences that play an important role in learning. 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. There have been given several definitions:

- "a predisposition on the part of some students to adopt a particular learning strategy regardless of the specific demands of the learning task" (Beshuizen and Stoutjesdijk, 1999)
- "the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment." (Keefe, 1979)
- "an individual's preferred approach to organizing and presenting information" (Riding and Rayner, 1998)

- "the way in which learners perceive, process, store and recall attempts of learning" (James and Gardner, 1995)
- "distinctive behaviors which serve as indicators of how a person learns from and adapts to his environment, and provide clues as to how a person's mind operates" (Gregorc, 1979)
- "a gestalt combining internal and external operations derived from the individual's neurobiology, personality and development, and reflected in learner behavior" (Keefe and Ferrell, 1990).

As we can see, learning style has been attributed several connotations in the literature. Learning styles can be seen as applied cognitive styles, removed one more level from pure processing ability usually referring to learners' preferences on how they process information and not to actual ability, skill or processing tendency (Jonassen and Grabowski, 1993). According to (Riding and Rayner, 1998), the key elements in an individual's personal psychology which are structured and organized by an individual's cognitive style are affect or feeling, behavior or doing, and cognition or knowing, and this psychological process is reflected in the way that the person builds a generalized approach to learning. The building up of a repertoire of learning strategies that combine with cognitive style, contribute to an individual's learning style (Papanikolaou et al., 2006).

3.1.2. Examples of Learning Style Models

There has been a great interest in the field over the past 20 years which led to the proliferation of proposed approaches. (Coffield et al., 2004a) 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:

- Allinson and Hayes' Cognitive Style Index (Allinson and Hayes, 1996)
- Apter's Motivational Style Profile (Apter, 2001)
- Dunn and Dunn's model and instruments of learning styles (Dunn and Griggs, 2003)
- Entwistle's Approaches and Study Skills Inventory for Students (Entwistle, 1998)
- Gregorc's Mind Styles Model and Style Delineator (Gregorc, 1985)
- Herrmann's Brain Dominance Instrument (HBDI) (Herrmann, 1996)
- Honey and Mumford's Learning Styles Questionnaire (Honey and Mumford, 2000)
- Jackson's Learning Styles Profiler (Jackson, 2002)
- Kolb's Learning Style Inventory (Kolb, 1999)
- Myers-Briggs Type Indicator (Myers and McCaulley, 1985)
- Riding's Cognitive Styles Analysis (Riding and Rayner, 1998)

- Sternberg's Thinking Styles Inventory (Sternberg, 1999)
- Vermunt's Inventory of Learning Styles (Vermunt, 1998)

These models differ in the learning theories they are based on, the number and the description of the dimensions they include. According to Curry's "Onion Model" (Curry, 1983), learning style models can be categorized into four layers: i) Personality Models – which focus on the personality traits of the learner and the way they influence the learning process; ii) Information Processing Models – which focus on the processes of acquiring, ordering and engaging with information; iii) Social Interaction Models – which focus on the collaborative aspects of the learning process; iv) Instructional Preference Models – which focus on the environmental, emotional and sociological preferences of the learner.

According to (Coffield et al., 2004a) there can be identified five families of learning styles:

- Genetic and constitutionally based factors
- Cognitive structure family
- Stable personality type
- Flexibly stable learning preferences
- Learning approaches and strategies.

In what follows we will describe in more detail four of the learning style models proposed in the literature, which will be further referred to in this thesis.

The first is *Ned Herrmann's Whole Brain Model* (Herrmann, 1996). According to it, the brain can be divided into 4 quadrants, each area having a model of thinking and learning associated to it:

- left cerebral – "theorists". They like facts, details, critical thinking, precise definitions, unambiguous instructions.
- left limbic – "organizers". They like step-by-step instructions, outlines, checklists, timelines, problem solving with clear steps and procedures.
- right limbic – "humanitarians". They prefer cooperative learning, group discussion, role-playing, personal approaches and examples.
- right cerebral – "innovators". They prefer brainstorming, metaphors, illustrations, pictures, synthesis, holistic approaches, alert rhythm.

According to *Felder-Silverman learning style model* (Felder and Silverman, 1988), learners are characterized by their preferences in four dimensions:

- active versus reflective learners
- sensing versus intuitive learners
- visual versus verbal learners
- sequential versus global learners.

Active learners learn by trying things out and enjoy collaborative working, while reflective learners like to think about the material first and prefer working alone. Sensing learners have a preference towards facts and details and they tend to be practical and

careful, whereas intuitive learners prefer abstract material, they like to innovate, to discover possibilities and relationships. Visual learners remember best what they see (pictures, diagrams, schemas etc) while verbal learners get more out of words, either spoken or written. 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.

Kolb's learning style model (Kolb, 1999) is based on his experiential learning theory, i.e. "learning is the process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of grasping experience and transforming it". According to Kolb, the cycle of learning includes four stages:

- Concrete Experience (CE)
- Reflective Observation (RO)
- Abstract Conceptualization (AC)
- Active Experimentation (AE)

which a student passes through during the learning process. The theory states that while almost every individual uses all learning modes to some extent, each person has a preferred learning style, determined by obtaining scores on the Concrete / Abstract and Active / Reflective dimensions and mapping them on a grid. The result is four learning styles (see Fig. 3.1):

- Diverging (CE/RO)
- Assimilating (AC/RO)
- Converging (AC/AE)
- Accommodating (AE/CE)

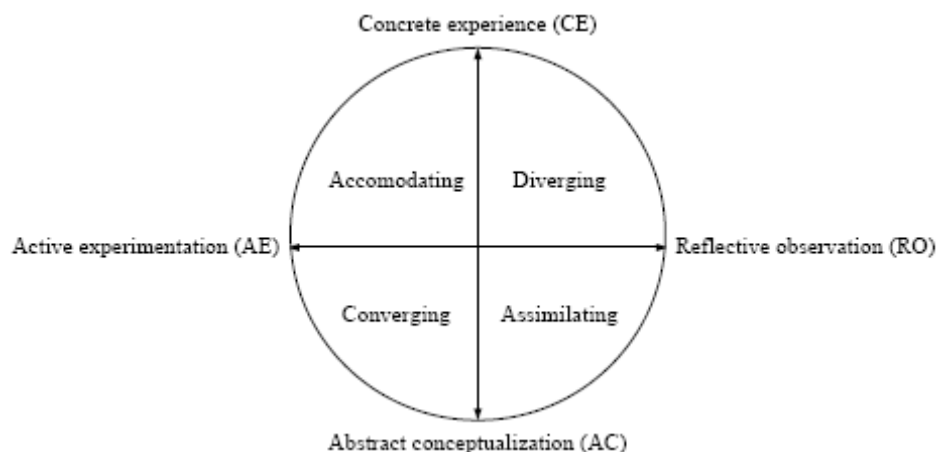


Figure 3.1. Kolb's learning style model

The converging learner is good at finding practical applications for ideas and theories, problem solving and decision making; she/he is controlled in the expression of

emotion and prefers dealing with technical problems rather than interpersonal issues. The diverging learner is imaginative and innovative, perceiving a situation from many perspectives; she/he is interested in people and tends to be feeling-oriented. The assimilating learner likes abstracts ideas and concepts, inductive reasoning, creating theoretical models, believing that it is more important for ideas to be logically sound than practical; she/he is more concerned with theories than with people. The accommodating learner likes hands-on activities, learning by doing, trial-and-error, new experiences and changing circumstances; she/he enjoys working with other people, but sometimes may be seen as impatient and "pushy".

Based on Kolb's theory, **Honey and Mumford** (2000) developed a new learning style model, including 4 styles (see Fig. 3.2):

- **Activists** – who are flexible and open-minded, ready to take action and like to be exposed to new situations; they sometimes take unnecessary risks, rush into action without sufficient preparation and get bored with the implementation / follow through.
- **Reflectors** – who are careful, thorough, methodical, good at listening to others and assimilating information; sometimes they tend to be too cautious and not take enough risks, to hold back from direct participation and they may be slow to make up their minds and reach a decision.
- **Theorists** – who are very logical, rational and objective, they are good at grasping the big picture and have a disciplined approach; they are intolerant of anything subjective or intuitive and have low tolerance for uncertainty, disorder and ambiguity.
- **Pragmatists** – who are practical, businesslike, technique-oriented, they want to test things out in practice and get straight to the point; they are not interested in theory or basic principles and tend to reject anything without an obvious application; they are impatient with decisions and more task-oriented than people-oriented.

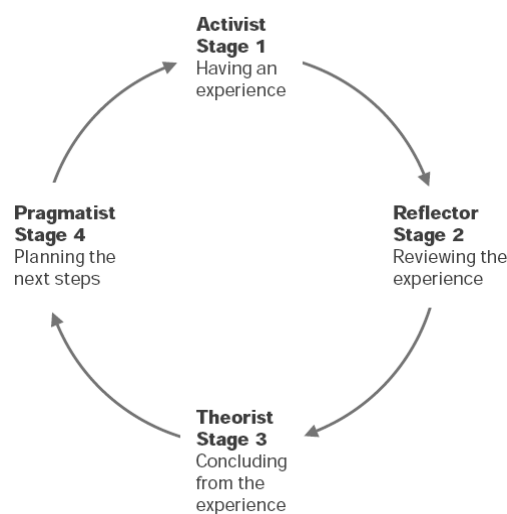


Figure 3.2. Honey and Mumford learning style model

All the above described models are included, according to Coffield et al.'s report, in the "flexibly stable learning preferences" family, i.e. their authors consider that learning style is not a fixed trait, but a "differential preference for learning, which changes slightly from situation to situation. At the same time, there is some long-term stability in learning style" (Kolb, 2000). We also adhere to this view of learning styles, that we will use further in this thesis.

Each of the above learning style models have an associated measuring instrument:

- Herrmann Brain Dominance Instrument, which includes 120 items on the basis of which the dominant quadrant (or quadrants) are identified.
- Soloman and Felder (1998) Index of Learning Styles questionnaire, which consists of 44 questions, each with two possible answers. As a result of the test, the learning style of the student is described on a scale between -11 and +11 (with a step of +/-2) for each FSLSM dimension.
- Kolb's Learning Style Inventory, which uses a forced-choice ranking method to assess an individual's preferred modes of learning (AC, CE, AE and RO), by means of 12 sentences that the subject has to complete.
- Honey and Mumford Learning Style Questionnaire, which consists of 80 items with true/false answers, that probe preferences for four learning styles, with 20 items for each style.

3.1.3. Implications for Pedagogy

Each of the learning style models includes 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 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" (Felder, 1993). (Dunn and Griggs, 2003) also suggests 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 (Grasha, 1984; Gregorc, 1984; Apter, 2001).

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"; individuals can be taught to monitor their selection and use of various learning styles and strategies. Moreover, as Apter (2001) suggests, an understanding of the various elements which produce different states of motivation in different contexts can "allow people to come more in control" of their motivation and hence of their learning. Students can become more effective in their learning if they are made aware of the important qualities which they and other learners possess (Coffield et al., 2004a). As Kolb (1999) put it: "Understanding your learning style type, and the strengths and weaknesses inherent in that type, is a major step toward increasing your learning power and getting the most from your learning experiences". Furthermore, "learning styles can provide learners with a much needed 'lexicon of learning' – a language with which to discuss, for instance, their own learning preferences and those of others, how people learn and fail to learn, why they try to learn, how different people see learning, how they plan and monitor it, and how teachers can facilitate or hinder these processes" (Coffield et al., 2004b).

3.2. Incorporating Learning Styles in Adaptive Educational Hypermedia

3.2.1. Specificity of Learning Style based Adaptive Educational Systems

Accommodating individual differences is an important goal of today's e-learning, whether it implies disabilities, a different knowledge level, technical experience, cultural background or learning style. This is also one of the advantages of e-learning over traditional, face-to-face learning: the increased potential of providing individualized learning experiences. Despite the importance given by specialists in educational psychology starting 3 decades ago, learning styles have only been introduced relatively recently in educational systems. During the last 5 years however, they began to receive special attention, and several learning style based adaptive educational systems started to appear.

LSAES are a special case of adaptive educational systems, which focus on students' learning preferences as the adaptation criterion. Most of the approaches in AES (which are usually based on student knowledge level) can also be applied to these systems; however they present several particularities, related to the large variety of learning style models that can be adopted and the inherent difficulty and subjectivity of the categorization.

As pointed out in Chapter 2, any AES involves two distinct processes or phases: student modeling and adaptation decision making. These processes are strongly interconnected, since adaptation decision making is based on the results provided by the student modeling component; however, they can also be seen as independent, since for the same learner model the system may use different adaptation logics. Thus any adaptive system can be decomposed in two relatively distinct parts: the modeling component and the adaptation component.

Generally, the existing LSAES focus more on one of the above processes: most of them start from asking the student to fill in a dedicated psychological questionnaire; the resulted membership to a particular learning style is stored once and for all in the student model kept by the system (explicit method). The system focus is then on the implementation of the adaptation logic, using a subset of the techniques identified in the previous chapter. A few systems also focus on the learner modeling process, trying to identify the student learning preferences implicitly, by monitoring and analyzing student behavior in the system.

Another important difference exhibited by the LSAES refers to the underlying learning style model. Most of the LSAES to date only take into account a single model. The systems can also be classified according to the modeling techniques used (data mining or machine learning algorithms), the number of modeled student characteristics besides learning preferences (knowledge level, goals) and the type, size and conclusions of the reported experiments.

One of the most widely used learning style models in LSAES is that proposed by Felder-Silverman in (Felder and Silverman, 1988) (FSLSM). The reasons behind its popularity are summarized by (Brown et al., 2006), who justify their choice for FSLSM with the fact that it fulfills most of the required criteria: i) the model should be able to quantify learning styles (and hence model them computationally); ii) the model should display a good degree of validity and reliability/internal consistency (and thus provide accurate evaluations of learning style); iii) the model should be suitable for use with an adaptive web-based educational system; iv) the model should be suitable for use with multimedia; v) the model should be easily administered to university students. Furthermore, as (Sangineto et al., 2007) noted, FSLSM was widely experimented and validated on an engineering student population. Moreover, although other models may have stronger theoretical foundations, FSLSM contains useful pragmatic recommendations to customize teaching according to the students' profiles.

These are the reasons why we also chose FSLSM for illustration purposes and for comparisons throughout this thesis. We start with some criteria that could be used for associating students with a preferred learning style of the FSLSM model, as summarized in Table 3.1.

<i>Parameter</i>	<i>Value</i>	<i>FSLSM Preference</i>
No. of visits/postings in forum/chat	High	Active, Verbal
No. of visits and time spent on exercises	High	Active, Intuitive
Amount of time dealt with reading material	High	Reflective
Performance on questions regarding theories	High	Intuitive
Performance on questions regarding facts	High	Sensing
Amount of time spent on a test	High	Sensing
No. of revisions before handing in a test	High	Sensing
No. of performed tests	High	Sensing
No. of visits and time spent on examples	High	Sensing
Amount of time spent on contents with graphics	High	Visual
Performance in questions related to graphics	High	Visual
Performance on questions related to overview of concepts and connections between concepts	High	Global
Performance on questions related to details	High	Sequential
Performance on tests in general	High	Sequential
No. of visits and time spent on outlines	High	Global
Navigation pattern	Skipping learning objects	Global
Navigation pattern	Linear	Sequential

Table 3.1. Correspondence between student actions and FSLSM preference

Next we illustrate some ways of providing adaptivity in an LSAES for students with different FSLSM preferences:

- a course for a sequential learner will include a step-by-step presentation of the content, with a very regular structure and with the links to related or more advanced subjects placed at the end of the course, in order not to distract the learner. The navigation will typically be done sequentially, by means of "Next" button which will therefore be highlighted and conveniently placed. The outlines will be hidden and the tests will be presented at shorter intervals.

- a course for a global learner will include outlines and summaries for each course item, which will be presented at the beginning and end of each chapter and will be permanently accessible through a menu. The links to related or complex topics will be integrated in the content, to help situate the learnt subject and contribute to create the big picture. The exercises will be placed at the end of the chapter, not after each course item, in order to give the users the opportunity to holistically understand the subject first.

- a course for active students will include multimedia objects (interactive animations and simulations), exercises (to provide practice opportunities), communication opportunities (forum/chat)
 - a course for reflective students will include less exercises and more time to study the course content
 - a course for sensing students will be focused more on facts, practical aspects and examples; it will include various multimedia objects
 - a course for intuitive students will contain less examples, the focus being on the abstract concepts and theories
 - a course for visual students will include plenty of multimedia objects based on video and images; the content will be presented as much as possible using graphics and schemas.
 - a course for verbal students will include audio materials and provide communication opportunities (forum, chat, audio- and video-conference).

It should be noted that moving from the FSLSM theory to the above adaptation strategies is an act of interpretation, since FSLSM, as any other learning style model, only makes teaching suggestions but not instructional prescriptions. Furthermore, some of the suggestions were conceived explicitly for traditional classroom education and had to be adapted for e-learning use.

3.2.2. Examples of LSAES

In what follows we will succinctly present some of the most representative LSAES to date. They are classified according to the learning style model that they employ. It should be noted that the list includes also educational systems that deal only with diagnosing the learning style of the students, without providing adaptation based on the identified student model.

As we already stated in the previous section, FSLSM is the most popular learning style model in AEHS. CS383 (Carver et al., 1999) is one of the first adaptive educational systems to take into consideration learning styles. More specifically, it is based on 3 constructs of the Felder-Silverman model (sensing/intuitive, visual/verbal, sequential/global), which are assessed by means of applying the Felder-Soloman's dedicated questionnaire. The adaptation is done at the presentation level by means of the sorting fragments technique (according to the suitability for each particular learning style).

Another example in the same category is the system proposed in (Bajraktarevic et al., 2003), that deals with the sequential/global dimension of the Felder-Silverman learning style model. Students are explicitly diagnosed by applying the Felder-Soloman Index of Learning Styles Questionnaire and are subsequently presented with the course content in a specific layout, corresponding to the identified preference. The reported

experiments also deal with mismatched learning style sessions, in order to contrast the results (learners' scores on evaluation tests, learner browsing time) with those obtained in the matched learning style sessions.

TANGOW (Paredes and Rodriguez, 2004) is another system which is based on two dimensions of FSLSM: sensing/intuitive and sequential/global. Learners are asked to fill in the ILS questionnaire when they log into the system for the first time and the student model is initialized correspondingly. Subsequently the student actions are monitored by the system and if they are contrary to the behavior expected for that learning preference, then the model is updated. Next, the students are presented with the instructional modules (i.e. "example", "exposition") in the order that corresponds to the created learner model.

Another AES that deals with Felder-Silverman learning model is Heritage Alive Learning System (Cha et al., 2006a; 2006b). Learning preferences are diagnosed implicitly, by analyzing behavior patterns on the interface of the learning system using Decision Tree and Hidden Markov Model approaches. Consequently the learning system interface is adaptively customized: it contains 3 pairs of widget placeholders (text/image, audio/video, Q&A board/Bulletin Board) each pair consisting of a primary and a secondary information area. The space allocated on the screen for each widget varies according to the student's learning style.

The system presented in (Sangineto et al., 2007) is also based on Felder-Silverman learning style model, and uses fuzzy values to estimate the preference of the student towards one of the four categories (Sensing-Intuitive, Visual-Verbal, Active-Reflective, Sequential-Global). A personalized learning path is created for each student, including those learning resources that correspond to the identified learning style.

Finally, (Graf, 2007) presents a way of extending Moodle learning management system with the capability of identifying student learning style, according to all four dimensions of the FSLSM. The actions of the students interacting with Moodle LMS are recorded and then analyzed using a Bayesian Network approach as well as a rule-based approach. Next the learning resources (i.e. examples, exercises, self assessment tests, content objects) are ordered according to students' preferences.

Another learning style model that was adopted by two educational systems is VARK (Flemming, 1995), which deals with the preferred perception modality of the students (Visual, Aural, Read/Write, Kinesthetic). Arthur system (Gilbert and Han, 1999) uses three learning preferences (Auditory, Visual and Tactile), while SACS (Style-based Ant colony system) (Wang et al., 2008) uses all four. iWeaver (Wolf, 2002) is also based on the perceptual preferences (Auditory, Visual – Pictures, Visual – Text, Tactile Kinesthetic, Internal Kinesthetic) but includes also four psychological learner preferences (Impulsive, Reflective, Global, Analytical), all of which are included in the Dunn & Dunn learning style model (Dunn and Griggs, 2003).

Honey and Mumford learning style model (Honey and Mumford, 2000) was used in INSPIRE educational system (Papanikolaou et al., 2003). The prevalence of the Activist, Pragmatist, Reflector or Theorist dimension is identified either by applying a dedicated questionnaire or by student's self-diagnosis (students can directly manipulate and modify their learner model). Subsequently, the system adapts the order and appearance of the instructional modules (i.e. Theory, Example, Activity, Exercise). The same learning style model was also used in Feijoo.net (Paule Ruiz et al., 2003).

Other learning style models that were included in LSAES are: Biggs' surface vs. deep student approach to learning and studying (Biggs, 1987) – used in (Stathacopoulou et al., 2007) and Witkin's field dependence/field independence (Witkin, 1962) – used in AES-CS (Triantafillou et al., 2003). Although not an actual learning style model, Gardner's theory of multiple intelligences (Gardner, 1993) is also worth mentioning here, with EDUCE (Kelly and Tangney, 2006) as its implementing system.

Finally, the AHA! system (Stash, 2007) is based on the notion of "instructional meta-strategies", by means of which the course authors can choose the learning styles that are to be used as well as the adaptation strategy. The AHA! system is thus independent of any particular learning style model. However, there is a limitation in the types of strategies that can be defined and consequently in the set of learning preferences that can be used. (Stash, 2007) includes examples of 3 instructional strategies (for verbalizer versus imager style; global versus analytic style; activist versus reflector style) and 2 meta-strategies (for inferring preference for text versus image and for navigation in breadth-first versus depth-first order).

More details regarding the above systems will be included in the following chapters: in Chapter 4 we will analyze them from the point of view of their modeling component, while in Chapter 5 we will review their adaptation component. In the next section we will introduce our own approach, namely a unified learning style model that integrates characteristics from several models in the literature.

3.3. Introducing a Unified Learning Style Model

3.3.1. Learning Style Criticism

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

The main problem, 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 (itself influenced by several factors); motivation; socio-economic background; time; effort; health (or lack of it); reinforcement; class environment etc they all contribute to how, when and under what

circumstances somebody learns. (Brown et al., 2007) borrowed the phrase "wicked problem", used by (Rittel and Webber, 1973) in the context of social planning, to describe the study of learning. "Wicked problems" are incomplete and contradictory, having changing constraints and resources; their solutions are often difficult to find, because of the complex interdependencies, and cannot be considered finite - they tend to be "better or worse" rather than "true or false". 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.

The reports published by Coffield et al. (2004a; 2004b) are 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 to the measuring instruments of the learning style models (which suffer from psychometric flaws), and not to the models themselves. The 13 main models identified were analyzed for evidence, provided by independent researchers, that the instrument 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: "The most telling argument, however, against any large-scale adoption of matching is that it is simply 'unrealistic, given the demands for flexibility it would make on teachers and trainers' (Reynolds, 1997). 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., 2004a). Obviously this problem is alleviated in the computer-based educational systems, which have the built-in potential of offering individualized learning paths to the students.

A further negative aspect outline by (Coffield et al., 2004a) is the theoretical incoherence and conceptual confusion, which comes precisely 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. Figure 3.3 illustrates some of the correlations that exist between various models. The field suffers from the lack of an overarching synthesis of the main models.

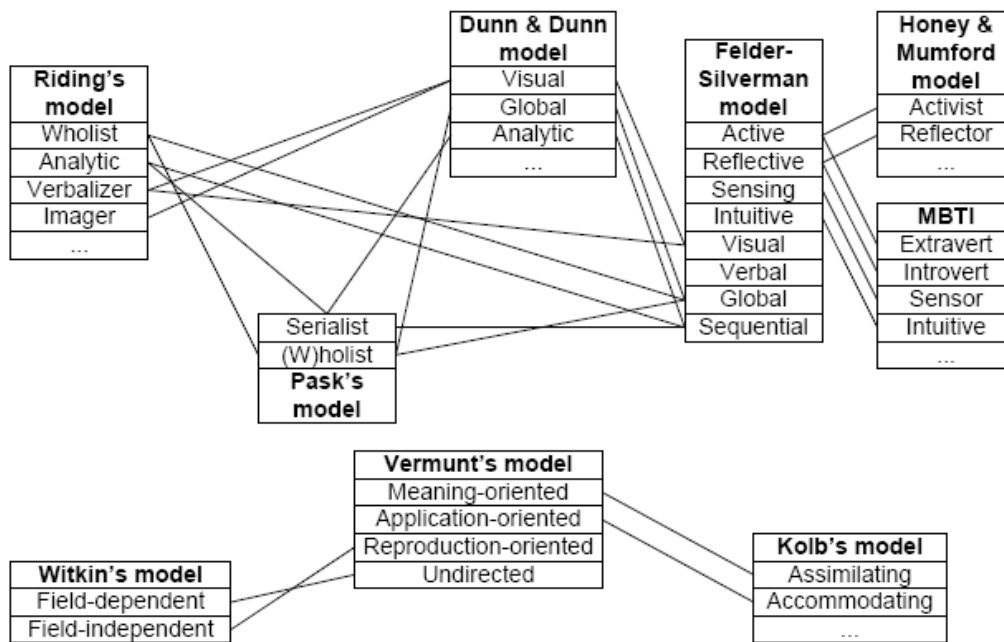


Figure 3.3. Correlations between learning style models (Stash, 2007)

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

Another criticism is related to the unjustified importance that practitioners attribute to learning styles. We cannot but agree with this point, especially in case that learning styles are preferred to the detriment of other more influential factors, such as reinforcement, student's prior cognitive ability, instructional quality etc. Given the complexity of the learning process, it is indeed very difficult to determine what percentage of the variance in student performance is attributable to learning styles. However, as most of the performed studies concluded, the students' perceived satisfaction was increased in case of individualized versus "one-size-fits-all" approach. 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.

Obviously, cost efficiency is an important factor when deciding the large scale use of this individualized approach. We should not forget that the aim of Coffield et al.'s reports is to give an advice over the adoption of mandatory use of learning styles in post-16 UK learning. In this context of traditional learning, the costs and efforts needed to implement learning styles are indeed quite important, while the educational system undoubtedly has also other needs: "Policy-makers and politicians also have important choices to make; for example, do they spend scarce resources on training all new and in-service teachers and tutors in learning styles; or would they better serve the cause of post-16 learning by using the same money to increase the new adult learning grants from the

low figure of £30 per week?" We need to understand Coffield et al.'s report in the light of its declared purpose, already included in the subtitle: "What research has to say to practice".

So actually Coffield et al. don't tell us that we should not try to individualize the learning experience to the learning style of the students; they just point out the existing body of evidence, which is not conclusive, so that more research should be done in this area. This is exactly what we try to do throughout this thesis. Should the field be crystal clear, no further research would have been needed.

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

Moreover, it should be pointed out that Coffield et al.'s reports only address learning styles from the traditional learning point of view, not discussing the implications of computer-based learning.

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, when using the matching/mismatching adaptation: (Carver et al., 1999), (Barker et al., 2000), (Bajraktarevic et al., 2003), (Papanikolaou et al., 2003), (Triantafillou et al., 2003), (Lee et al., 2005), (Graf, 2007), (Sanginetto et al., 2007), (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: (Mitchell et al., 2004), (Brown et al., 2006), (Brown et al., 2007). A short review of these studies is included in Chapter 5. However, as the authors themselves concede, no definitive conclusion 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-optimal opportunities (i.e. a mismatched environment).

We agree with Coffield et al.'s conclusion that "it is simply premature (and perhaps unethical) to be drawing simple implications for practice when there is so much complexity and so many gaps in knowledge". It is the aim of this thesis to try to fill in some of these gaps.

Indeed, in what follows we try to address most of the criticism aspects, by proposing:

- an integrator model, which includes characteristics from the major models proposed in the literature, thus establishing a unified core vocabulary

- an implicit modeling method, based on the direct observation and analysis of learner behavior, thus avoiding the psychometric flaws of the measuring instruments
- a dynamic modeling method, based on continuous monitoring and analysis of learner behavioral patterns, which is in line with the flexibly stable approach
- a simple description of the learning preferences, with no danger of labeling or pigeonholing the students
- a more pragmatic approach, with instructional prescriptions for each learning preference.

3.3.2. Justifying the Use of a Unified Learning Style Model

Current Challenges

As we have already stated, the learning styles are a controversial subject. The most frequently raised criticisms are:

- There is a very large number of learning style models proposed (over 100 according to (Mitchell, 1994), 71 worth of consideration according to (Coffield et al., 2004a)) and there is no unanimously accepted learning style model.
- There is a proliferation of terms and concepts; some researchers do not give clear definitions to their key concepts, using terms loosely and interchangeably. Concepts in learning style models 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.
- Questionnaires can be done only once; furthermore it is difficult to motivate students 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, 2000).
- 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. Some experiments have already been conducted to test the dependency among learning styles and technology preferences (Klicek and Zekic-Susac, 2003).

Learning systems that include a *dynamic modeling component* alleviate some of the above problems. Indeed, according to many researchers, observations and interviews are more likely than instruments to capture the learning preferences of a student (Coffield et al., 2004a). Thus implicit student 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. Moreover, this approach could also prove beneficial to the learning style research area: large scale experiments (greatly facilitated by the use of learning systems) will allow contrasting and comparing the categorizations obtained through questionnaires with those obtained by means of analyzing behavioral patterns. The results will contribute to the necessary improvement of the classical psychological questionnaires and the underlying theories.

As we have seen in previous sections, there are a few attempts at dynamic student modeling. However all these systems only deal with a single learning style model, still being subject to the first two weaknesses outlined above.

Towards a Different Approach

The novelty of our approach consists in the proposal of a *unified learning style model (ULSM)*, specifically adapted for e-learning use. This model should include learner characteristics from various learning styles models, which meet three conditions:

- have a significant influence on the learning process (according to the educational psychology literature)
- can be used for adaptivity purposes in an educational hypermedia system (i.e. the implications they have for pedagogy can be put into practice in a technology enhanced environment)
- can be identified from student observable behavior in an educational hypermedia system: i) navigational indicators (number of hits on educational resources, navigation pattern); ii) temporal indicators (time spent on different types of educational resources proposed); iii) performance indicators (total learner attempts on exercises, assessment tests). Indeed, not all of the characteristics included in a classic learning style model can be identified through an educational hypermedia system, nor can they be used for adaptation.

As we have seen in the previous sections, there is much overlap between learning style models. Cassidy (2003) 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. Whether stable or flexible, whether psychological traits or strategies, whether genetically determined or experience-related, all categories of learning styles have been claimed to exert an influence on learning. So instead of arguing over the best learning style, it is undoubtedly better to take the best of each model and use a complex of features, each with its own importance and influence.

3.3.3. Description of the Unified Learning Style Model

In this context, our intention is to offer a basis for an integrative learning style model, by gathering characteristics from the main learning styles proposed in the literature. We can thus summarize 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

(a revised version of the ULSM presented in (Popescu et al., 2007a))

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 learning style model, including its name and its intensional definition. The "active experimentation / reflective observation", refers to only a part of the intensional

definition of "active / reflective" FLSM dimension, 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 learning style models, but it is included as a characterizing trait in many of them (e.g. sequential / global or sensing / intuitive dimension of FLSM).

That being said, 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: Felder and Silverman model (visual / verbal dimension), VARK (visual, aural, read/write, kinesthetic), VAK (visual, auditory, kinesthetic), Dunn and Dunn model (visual, auditory, kinaesthetic, tactile), Riding's model (verbaliser / imager) 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 Felder and Silverman: 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), as well as Gregorc's model (abstract / concrete). 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 the Felder-Silverman model (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 FLSM (active / reflective) or Honey and Mumford model (activist / reflector).

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. 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 FLSM: inductive learners prefer to reason from particular facts to a general conclusions;

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), 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, to which the "resistant" component was added, which is similar to Grasha-Riechmann's "avoidant" (Grasha, 1995) and Vermunt's "undirected". Students with a deep approach to learning are "meaning-oriented", they want to understand ideas for themselves, they relate ideas to previous knowledge and experience, 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, they manage time and effort effectively, 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. 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 FLSM active / reflective dimension, Herrmann's theorist vs. humanitarian).

The introvert vs. extravert characteristic is taken from the Myers-Briggs Type Indicator (extraversion / introversion), 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 (Grasha, 1995), being also correlated with Apter's concept of autistic 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 learning 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, mobility), can only be catered for in traditional learning settings. Hence, while having an important effect on learning, they are outside the scope of this thesis.

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.

Furthermore, we should underline the pragmatic character of the ULSM model. Since we are not psychologists, our intention was not to propose yet another learning style model, but to summarize those characteristics that could have a practical use in web-based educational systems. From a theoretical point of view, a systematic and rigorous classification of the concepts involved would be necessary, together with an associated measuring instrument, which should be empirically validated. However this is outside the scope of this thesis. Hence the value of our model lies not in its theoretical grounds but in its practical use.

3.3.4. Advantages of Our Implicit Modeling Method using ULSM

First, the problems related to the multitude of learning style models, the concept overlapping and the correlations between learning style dimensions are solved. Thus researchers will no longer have to face the debate related to the choice of the best

available learning style model (none of them being actually comprehensive enough to include all learning preferences).

Moreover, the limitation imposed by traditional learning in the number of learning style dimensions that can be taken into consideration is removed through the use of technology enhanced systems. Actually one of the advantages of e-learning is the inherent suitability to offer personalized learning solutions, accommodating individual differences. Thus the ULSM will be able to include a large number of learning preferences, without an increase in the teacher workload. In traditional learning, 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 hypermedia systems, the teacher will have to prepare the same amount of educational materials, which will be dynamically combined according to each student's preferences. Hence another advantage of our approach is a finer granularity of the student classification (which in turn triggers a more effective adaptation).

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, 1991). 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 will show in Chapter 5.

Another advantage of the ULSM is a simplified and more accurate student categorization (*feature-based modeling*). Thus, what will be actually stored by the system is not the membership to a particular learning style model (*stereotype-based modeling*), but instead a set of learning preferences that will drive adaptation. Indeed, there is no point in using various observed student preferences (e.g. individual vs. team work, graphics vs. text, spoken vs. written words, concepts vs. facts, theory vs. examples, step-by-step vs. global approach, careful vs. not careful with detail etc.) to infer categorization into a certain learning style and then use for adaptation the preferences theoretically associated to that particular category. Instead it is easier, more pointed and more meaningful to directly store the student preferences. Thus problems related to dependencies between learning style dimensions are overcome and the adaptation can be done with regard to each of the directly observed (not deduced) student preferences.

Moreover, 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.

Furthermore, 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.

In case of dynamic modeling, the student's style is not assessed only once, at the beginning of the course. On the contrary, the student's behavior is continuously monitored so that the changes in her/his learning style can be detected and the adaptation strategy modified accordingly (e.g. a student may be best taught by one method early in learning and by another after the student has gained some competence).

Finally, the pedagogical model and the student model are independent: various adaptation actions can be associated with each learner model, depending on the intended pedagogical goal: i) increase student's self-awareness about her/his strengths and weaknesses in the learning process (open model approach); ii) offer the student a learning experience that matches her/his preferences; iii) deliberately mismatch instructional approach to provide challenge and/or to develop alternate student skills. Apart from the intensional definitions (descriptive information), we need to provide prescriptive guidelines, which can be translated into adaptation strategies. This is especially important in case of a pragmatic model like ULSM. However, as learning styles models are usually rather descriptive in nature, offering only general recommendations regarding the most suitable instructional method, we had to go through a process of interpretation of these recommendations. The result of this process is presented in the form of adaptation rules in Chapter 5.

In this chapter we introduced a unified learning style model and theoretically justified its use. In the next two chapters we will practically demonstrate how it can be used in an automatic learner modeling process (Chapter 4) as well as in a dynamic adaptation process (Chapter 5).

Chapter 4

Modeling the Learner

from the Learning Style Point of View

As we pointed out in chapter 2, modeling the learner is the first step towards providing a learning experience that is individualized to the particular needs and characteristics of the learner (which in the context of this thesis refer to the learning preferences and learning styles). We therefore need a method for accurately diagnosing the learning style of the student. We start this chapter with a short review of the methods that have been proposed in the literature to this end: while the majority of the current LSAES use dedicated psychological questionnaires for identifying the learning preferences of the students, there are some systems that also use an implicit modeling method, based on analyzing the behavior of the students in the system. Our approach is included in the latter category.

However, according to (Paule Ruiz et al., 2008), this implicit modeling method presents a challenge, in that it is difficult to determine what are the learner actions that are indicative of a particular learning style. This is why we performed two experimental studies, trying to identify correlations between students' patterns of behavior and their learning preferences; the results of the inferential statistical analysis that was performed on the data collected from the students' interaction with our dedicated educational system (WELSA) are presented and discussed in the second section of this chapter.

Next, based on these findings as well as on the data collected from the literature, we conceived a rule-based method for diagnosing student learning preferences included in ULSM. The third section of this chapter introduces this method, as well as the experimental results that were obtained by applying it on our WELSA system.

Finally, once we have identified the learning preferences from ULSM we can use them to categorize the student in one of the traditional learning style models. The applicability of the approach is illustrated in section 4.4, with three of the most popular models: Felder-Silverman learning style model (Felder and Silverman, 1988), Herrmann Whole Brain Model (Herrmann, 1996) and Kolb learning style model (Kolb, 1999).

4.1. Critical Review of Existing Approaches

In chapter 3 we briefly introduced the state-of-the-art learning style based educational systems. In this section we focus on the methods used for learner modeling and we classify the systems in two categories: those that use questionnaires for identifying the learning style and those that use students' observable behavior.

4.1.1. Explicit Modeling Method

The first adaptive educational systems that dealt with learning styles as adaptation criterion relied on the measuring instruments associated to the learning style models for diagnosing purposes. The main advantage of this method is its simplicity: the teacher / researcher only has to apply a dedicated psychological questionnaire, proposed by the learning style model creators. Based on the students' answers to the questions, a preference towards one or more of the learning style dimensions can be inferred. The main disadvantages of this questionnaire-based approach are:

- some of the measuring instruments used could not demonstrate internal consistency, test-retest reliability or construct and predictive validity, so they may not be totally reflective of a way a particular student learns
- it implies a supplementary amount of work from the part of the student, who has to fill in questionnaires at the beginning of the course (which sometimes may include over 100 questions, as in case of the Herrmann's Whole Brain Model)
- it can be easily "cheated" by the students, who may choose to skip questions or give wrong answers on purpose
- there can be non-intentional influences in the way the questions are formulated, which may lead the students to give answers perceived as "more appropriate"
- it is difficult to motivate the students to fill out the questionnaires; especially if they are too long and the students are not aware of the importance or the future uses of the questionnaires, they may tend to choose answers arbitrarily instead of thinking carefully about them
- it is static, so the student model is created at the beginning of the course and stored once and for all, without the possibility to be updated.

A method of improving this approach is to give the student the possibility to modify her/his own profile, if she/he considers that the one inferred from the questionnaire results is not appropriate (does not correspond to the reality). This is called an "open model" (scrutable and modifiable) approach and it is used either in conjunction with the questionnaires or in place of them. This direct access of students to their own learner model has several advantages: it provides an increased learner control, it helps the learners develop their metacognitive skills and it also offers an evaluation of the quality of the model created by the system (Kay, 2001). The main disadvantages of this approach are that it increases the cognitive load of the student and that it must rely on the self-evaluation of a student who might not be aware of her/his learning style.

Examples of systems that use this explicit modeling method are:

- CS383 (Carver et al., 1999) – uses the Felder-Soloman Index of Learning Styles dedicated questionnaire in order to assess 3 constructs of the Felder-Silverman model (sensing/intuitive, visual/verbal, sequential/global).

- AES-CS (Triantafillou et al., 2003) – uses a Group Embedded Figures Test questionnaire at the beginning of the course, in order to assess the field dependence/field independence characteristic of the learner.
- (Bajraktarevic et al., 2003) – uses the Felder-Soloman Index of Learning Styles Questionnaire in order to assess the sequential/global dimension of the Felder-Silverman learning style model.
- Feijoo.net (Paule Ruiz et al., 2003) - uses the CHAEA Test (Alonso et al., 2002) for classifying the students in one of the four learning styles it proposes: Active, Reflective, Theoretical, and Pragmatic (based on the Honey and Mumford learning style model).
- INSPIRE (Papanikolaou et al., 2003) – is based on Honey and Mumford learning style model. The prevalence of the Activist, Pragmatist, Reflector or Theorist dimension is identified either by applying a dedicated questionnaire or by student's self-diagnosis, since students can directly manipulate and modify the learner model.
- The SACS (Style-based Ant Colony System) (Wang et al., 2008) - is based on the VARK style, which is identified by means of a dedicated questionnaire or input by the student.

4.1.2. Implicit Modeling Method

There is also a second category of systems, which use an implicit and/or dynamic modeling method. Three different approaches have been identified in this respect:

- analyze the performance of the students at evaluation tests - a good performance is interpreted as an indication of a style that corresponds to the one currently estimated and employed by the system; while a bad performance is interpreted as a mismatched learning style and triggers a change in the current learner model
- ask the students to provide feedback on the learning process experienced so far and adjust the learner model accordingly
- analyze the interaction of the students with the system (browsing pattern, time spent on various resources, frequency of accessing a particular type of resource etc) and consequently infer a corresponding learning style.

Sometimes, these systems use a mixed modeling approach: they first use the explicit modeling method for the initialization of the learner model and then the implicit modeling method for updating and improving the learner model.

Some examples of systems in this implicit modeling category include:

- Arthur system (Gilbert and Han, 1999) uses Auditory, Visual and Tactile learning preferences (basically a VAK learning style model); it divides the courses in concepts; when the student has finished with the first concept which was presented using a learning style that was chosen at random, the system assesses the student's success, and if this is not higher than 80%, the system changes her/his learning style.

- iWeaver (Wolf, 2002) – is based on the Dunn & Dunn learning style model, including five perceptual (Auditory, Visual – Pictures, Visual – Text, Tactile Kinesthetic, Internal Kinesthetic) and four psychological learner preferences (Impulsive, Reflective, Global, Analytical). When the learner first enters the environment, they fill in the Building Excellence Survey. Then the learner is given an explanation of their assessed learning style and recommendations on a media representation for the first content module and also the option to choose another media representation than the one that was recommended for their style. Also, after each module, the learner is asked for feedback on the media representations they encountered and for a ranked rating, which is used to adjust the learner model.

- TANGOW (Paredes and Rodriguez, 2004) – the system is based on two dimensions of FSLSM: sensing/intuitive and sequential/global. Learners are asked to fill in the ILS questionnaire when they log into the system for the first time and the student model is initialized correspondingly. Subsequently the student actions are monitored by the system and if they are contrary to the behavior expected for that learning preference, then the model is updated. The student observed behavior is restricted to 4 patterns, each corresponding to one of the four possible FSLSM preferences.

- Heritage Alive Learning System (Cha et al., 2006a) – is based on Felder-Silverman learning style model. Learning preferences are diagnosed implicitly, by analyzing behavior patterns on the interface of the learning system using Decision Tree and Hidden Markov Model approaches.

- EDUCE (Kelly and Tangney, 2006) is based not on a learning style model but on Gardner's theory of multiple intelligences (MI), using 4 types: logical/mathematical, verbal/linguistic, visual/spatial, musical/rhythmic (Gardner, 1993). The student diagnosis is done both dynamically (by analyzing the student's interaction with MI differentiated material and using a naïve Bayes classification algorithm) and statically (by applying a Shearer's MI inventory (Shearer, 1996)).

- (Stathacopoulou et al., 2007) is based on Biggs' surface vs. deep student approach to learning and studying (Biggs, 1987). The student diagnosis is done by means of a neural network implementation for a fuzzy logic-based model. The system learns from a teacher's diagnostic knowledge, which can be available either in the form of rules or examples. The neuro-fuzzy approach successfully manages the inherent uncertainty of the diagnostic process, dealing with both structured and non-structured teachers' knowledge.

- The system presented in (Sanginetto et al., 2007) is based on Felder-Silverman learning style model, and uses fuzzy values to estimate the preference of the student towards one of the four categories (Sensing-Intuitive, Visual-Verbal, Active-Reflective, Sequential-Global). Initially, the system offers to the learner the possibility to use the Soloman and Felder's psychological test or to directly set the values of the category types, choosing an estimated value for each category (using a slider-based interface).

Also, for those people who do not want or are not able to estimate their own learning styles, the system sets the initial values of all the category types to 0.5, which means that the student is initially evaluated as indifferent with respect to any learning style preference. Next the learning style is automatically updated by the system taking into account the results obtained by the students at the multiple-choice tests presented at the end of each learning phase.

- AHA! (version 3.0) (Stash, 2007) – uses the notion of "instructional meta-strategies" (inference or monitoring strategies), which are applied in order to infer the learner's preferences during her/his interaction with the system. A meta-strategy can track student's learning preferences by observing her/his behavior in the system: repetitive patterns such as accessing particular types of information (e.g. textual vs. visual format) or navigation patterns such as breadth-first versus depth-first order of browsing through the course. These meta-strategies are defined by the authors, who can therefore choose the learning styles that are to be used as well as the adaptation strategy. However, there is a limitation in the types of strategies that can be defined and consequently in the set of learning preferences that can be used, so these strategies cannot completely replace existing psychological questionnaires.

- (Garcia et al., 2007) – based on three dimensions of the FLSM (active/reflective, sensing/intuitive, and sequential/global). The behavior of students in an educational system (called SAVER) is observed and the recorded patterns of behavior are analyzed using Bayesian Networks.

- (Graf, 2007; Graf and Kinshuk, 2008) – is based on the Felder-Silverman learning style model. The actions of the students interacting with Moodle LMS are recorded and then analyzed using a Bayesian Network approach as well as a rule-based approach. Since the accuracy of the diagnosis was better in the latter case, the rule-based approach was implemented into a dedicated tool called DeLeS, which can be used to identify the learning style of the students in any LMS.

The systems that are closest to our approach are those that identify the learning styles by analyzing the interaction of the students with the educational system, in the form of behavioral patterns, namely (Cha et al., 2006a), (Garcia et al., 2007) and (Graf, 2007). The main advantages of our approach versus these related works are:

- All three related systems use the Felder-Silverman learning style model, while we use a combination of learning styles (the Unified Learning Style Model introduced in Chapter 3). Furthermore, we can also use the FLSM model starting from our ULSM (as we will show in section 4.4).

- The number of patterns of behavior that are taken into account in WELSA is larger (11 patterns in (Garcia et al., 2007), 39 in (Graf, 2007) and 58 in (Cha et al., 2006a) versus over 100 in WELSA) which should imply a higher precision of the learning style diagnosis (as we will see in section 4.3). This large number of patterns is due to the fine

granularity of learning objects which allows for a rich and precise annotation, as we will see in Chapter 6.

The methods used for learning style identification are also different: Decision Trees and Hidden Markov Models in case of (Cha et al., 2006a), Bayesian networks in case of (Garcia et al., 2007) and a rule-based approach in case of (Graf, 2007). It should be also noted that (Graf, 2007) deals with an existing learning management system (Moodle) that was enhanced with modeling and adaptation capabilities, while our work is based on our own adaptive educational hypermedia system (WELSA), that we have built from scratch.

The main challenge of these systems is to select those student actions that are indicative of their learning styles (Paule Ruiz et al., 2008). This is why the next section of the thesis focuses on identifying the correlations that exist between the students' patterns of behavior and their learning preferences. Proving that there can be found statistically significant relations between the learning style and the actual learning behavior in the system is also a further proof of the validity of our ULSM model.

4.2. Analyzing the Behavior of Students in an Educational Hypermedia System

According to the proponents of learning style models, students with different learning styles have different needs and also different behavior during the learning process. However, most of the learning style models that have been proposed in the educational psychology literature are conceived for traditional face-to-face educational settings, not for computer mediated instruction. This is why in this chapter we investigate the interaction of students with a web-based educational system (WELSA), trying to identify correlations between students' behavior and their learning styles.

A similar study has been performed by (Graf and Kinshuk, 2008), leading to some promising results. However, that study was performed in a learning management system (Moodle) and was based on the Felder-Silverman learning style model. Our study is performed with our own educational hypermedia system (WELSA) and based on the preferences in ULSM. However, our results can be generalized for any educational system in which the students may exhibit the same patterns of behavior (based on a common set of functionalities of the system).

4.2.1. Patterns of Behavior

Tracking the Interaction of the Learner with the Educational Hypermedia System

Analyzing and interpreting user log files is a valuable source of information

about the characteristics of the user (interests, preferences, goals etc). In the context of e-learning, tracking the interaction of the learner with the educational system has been used as an implicit and dynamic method for identifying the knowledge level, motivation and goals of the learners. More recently, these tracking data have started to be used for identifying also the learning style of the students (Cha et al., 2006a; Garcia et al., 2007; Stathacopoulou et al., 2007; Graf and Kinshuk, 2008).

According to (Stathacopoulou et al., 2007), student's behavior in a technology-enhanced learning environment refers to a student's observable response to a particular stimulus in a given domain. The response, together with the stimulus, serves as the primary input to the student modeling system (Sison and Shimura, 1998). Human tutors also use diagnostic evidence to adapt their instruction; however, the information human tutors can obtain from observing students is much richer, including not only a student answer to a question but also the timing of the student's response, the way of delivering a response, her/his tone of voice, hesitancy etc (Derry and Potts, 1998). Since the communication channel between a student and a web-based learning system usually includes only a keyboard and a mouse, the information that can be obtained is limited; however, it can be enhanced by an appropriately designed interface, which allows collection of all the available information about the student (i.e. each and every keystroke and mouse move). Of course, the communication channel could be extended with such devices as an eye tracker or a video camera or even more sophisticated devices that could monitor student's physical state (brain activity, heart rate, stress level). However, for the context of this thesis we will focus solely on the largely available educational systems, which only require a keyboard and a mouse.

Learner observable behavior in such an educational hypermedia system includes navigational, temporal and performance indicators, such as: number of hits and time spent on different types of educational resources, navigation pattern, total learner attempts on exercises, results obtained on assessment tests etc.

Relating Students' Behavior with ULSM Preferences

Based on the intensional definition of ULSM, as provided in chapter 3, as well as on the findings in related works (Cha et al., 2006a; Garcia et al., 2007, Graf and Kinshuk, 2008), we realized a mapping between the student behavior in face-to-face environments and the behavior in web-based environments. We hence came with the indicators that could be associated with each specific learning preference, as summarized in Table 4.1 (Popescu et al., 2008g).

Learning preference	Behavioral indicators
<i>Perception modality</i>	
Visual preference	High amount of time spent on contents with graphics, images, video High performance in questions related to graphics
Verbal preference	High amount of time spent on text and audio content High performance in questions related to written text High number of visits/postings in forum/chat High participation in audio conferences
<i>Processing information</i>	
Abstract concepts and generalizations	Access of abstract content first (concepts, definitions) High amount of time spent on abstract content High performance on questions regarding theories
Concrete, practical examples	Access of concrete content first (examples) High amount of time spent on concrete content High performance on questions regarding facts
Serial	Linear navigation (intensive use of Next – Previous buttons) Seldom access of additional explanations (related concepts)
Holistic	Non-linear navigation pattern (frequent page jumps) High amount of time spent on outlines, summaries, table of contents Frequent access of additional explanations (related concepts) High performance on questions related to overview of concepts and connections between concepts
Active experimentation	Access of practical content (simulations, exercises, problems...) before theory High number of accesses to exercises High amount of time spent on simulations and exercises
Reflective observation	Access of theoretical content before practical content Higher time spent on reading the material than on solving exercises or trying out simulations
Careful with details	High amount of time spent on taking a test High number of revisions before handing in a test High performance on questions regarding details
Not careful with details	Low number of revisions before handing in a test Low performance on questions regarding details
<i>Reasoning</i>	
Deductive	Access of abstract content first (concepts, definitions) High performance on exercises requiring direct application of theory
Inductive	Access of concrete content first (examples) High performance on exercises requiring generalizations
<i>Organizing information</i>	
Synthetic	High performance on exercises requiring synthesis

	competency Breadth first navigation pattern
Analytic	High performance on exercises requiring analysis competency Depth first navigation pattern
<i>Motivation</i>	
Deep approach	High amount of time spent on studying High engagement in study activities (frequent access to additional resources, frequent returns to the educational material, high number of visits/postings to forum/chat) High performance on tests
Surface approach	Low amount of time spent on studying Access of tests before studying the course material Solving of exercises by trial and error Medium performance on tests
Strategic approach	Time spent on studying mainly before exams Very active participation to forum/chat in order to get noticed by the teacher Seldom access to additional resources High performance on tests
Resistant approach	Very low amount of time spent on studying Lack of engagement (no participation to forum/chat, few accesses to resources) Very low performance on tests
<i>Persistence</i>	
High persistence	High amount of time spent on studying High number of test retakes High number of returns to educational material
Low persistence	Low number of test retakes correlated with low number of returns to educational material Frequent use of hints and answer keys
<i>Pacing</i>	
Concentrate on one task at a time	Low number of web browsers opened at a time Linear navigation path (few jumps and returns)
Alternate tasks and subjects	Frequent passages from one section of the course to another (educational material, communication tools, tests...) and from one course to another High number of web browsers opened at a time and frequent passages between them High non-linearity degree of the navigation path
<i>Social aspects</i>	
Introversion	Passive participation in communication channels Higher number of visits/postings in forum versus chat
Extraversion	Active participation in synchronous communication channels (chat, audio conference etc)
Individual work	Choice of individual assignments Seldom use of ask/offer peer help facility
Team work	Choice of group assignments

	Frequent use of ask/offer peer help facility High number of visits/postings in forum/chat
Competitive	Choice of individual assignments Seldom use of ask/offer peer help facility
Collaborative	Choice of group assignments Frequent use of ask/offer peer help facility
<i>Field dependence / independence</i>	
Field dependence	Breadth first navigation pattern Frequent use of navigation and orientation support (e.g. annotated links)
Field independence	Depth first navigation pattern Frequent use of index tool (non-linear navigation)

Table 4.1. Examples of student actions that could be used as indicators of learning preferences in ULSM

According to (Dolog et al, 2007), "an event is a record in the database with the information on certain actions performed by particular users with a specific learning object, together with the corresponding timestamp". Examples of such events that can be monitored and recorded by the system are: *login*, *logout*, *home*, *jumpToCourse*, *jumpToChapter*, *jumpToPage*, *nextButton*, *prevButton*, *outline*, *accessLO*. As seen from Table 4.1, the main behavioral indicators refer to the relative frequency of these learner events, the amount of time spent on a specific event type and the order of navigation, all of which can be obtained from the system log, either directly or after some preprocessing.

More specifically, the behavioral patterns that we will take into account in our analysis 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
- 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.

Defining Behavioral Patterns and Associating Them with ULSM

Based on the available data in a usual web-based learning environment and the indications from the literature regarding relevant behavioral indicators we decided to use the following set of patterns (where the prefix "n" stands for "number", "t" stands for "time" and "h" stands for "hits"):

- *t_total* - total time spent on the course
- *action_total* - total number of actions performed while logged in

- $t_instructionalType$ and $t_mediaType$ - the time spent on each type of LO, where $instructionalType = 'Definition', 'Example', 'Exercise'$ etc and $mediaType = 'Text', 'Sound', 'Image', 'Video'$ etc. In this respect, $t_abstract$ and $t_concrete$ are also computed, as the time spent on LOs with a rather abstract versus concrete content.

- $h_instructionalType, h_mediaType$ – the number of hits (visits) on each category of LOs.

- $n_LO, n_distinctLO, n_skippedLO_temp, n_skippedLO_perm$ - total number of hits on LOs, total number of distinct LOs accessed, number of LOs skipped temporarily or on a permanent basis respectively.

- the order of accessing the LOs is also relevant, being captured in the form of instructional role sequences: $sequence_fundamental_before_illustration, sequence_illustration_before_fundamental, sequence_abstract_first, sequence_concrete_first, sequence_exercise_last, sequence_interactivity_before_fundamental, sequence_interactivity_before_illustration, sequence_fundamental_before_interactivity, sequence_illustration_before_interactivity, sequence_tests_before_learningMaterial$

- $n_navigationAction$ - number of navigation actions of a specific type (e.g. $n_jump, n_jumpCourse, n_nextButton, n_prevButton, n_Outline, n_passageBetweenBrowsers, n_passageBetweenSections$)

- $t_chat, n_msg_chat, n_chat_login$ – total time spent in chat, number of messages in chat and number of logins into the chat respectively; $t_forum, n_forum_login, n_forum_msg, n_forum_reads$ – total time spent in forum, number of logins into the forum, number of messages posted in the forum and number of messages read in the forum respectively; $n_askPeerHelp, n_offerPeerHelp$ – number of times a student asks a colleague for help on solving a problem or understanding a concept and number of times a student offers help to a colleague. This can be in the form of either forum posts and/or special "Peer help" boards, dedicated to asking/providing peer assistance.

- $grade_tests$ – grades obtained on evaluation tests. We are also interested in the performance of students in some particular types of assessment tests, which are reflected in the following indicators: $grade_mediaType, grade_abstract, grade_concrete, grade_details, grade_overview, grade_connections, grade_directApplication, grade_generalizations, grade_synthesis, grade_analysis$. The total time spent on taking a test (t_test), the number of revisions performed on each test ($n_revisions_test$), the number of test retakes ($n_testRetakes$), the number of mistakes made when taking a test ($n_mistakes_tests$), as well as the number of hints used in solving a test (n_hints) can also offer indications of the student's learning style.

- $n_individualAssignment, n_groupAssignment$ - choice of individual assignments versus collaborative assignments.

We can also compute *relative values* for the above patterns, such as the percentage of time spent on each category of LOs (e.g. $t_instructionalType / t_total_LO *$

100), the relative frequencies of LO visits (e.g. $h_mediaType / n_LO$), the number of Next button clicks over the total number of navigation actions, the grade obtained on test items requiring synthesis competencies versus the average grade obtained in the course etc. In what follows we will use these relative values rather than the absolute ones since they are more meaningful (e.g. knowing the amount of time a student spent on images is only relevant in the context of her/his total study time). Please note that for reasons of simplicity we will use the above pattern names to denote also the relative values.

We will illustrate the above approach with some examples of patterns that could be put in relation with a subset of the ULSM learning preferences from Table 4.1.

Learning preference	Patterns
Visual preference	t_Image + t_Video, h_Image + h_Video grade_Image
Verbal preference	t_Text + t_Sound, h_Text + h_Sound grade_Text n_chat_msg, n_chat_login, t_chat n_forum_login, n_forum_msg, n_forum_reads, t_forum
Abstract concepts and generalizations	sequence_fundamental_before_illustration sequence_abstract_first t_Fundamental + t_Definition, h_Fundamental + h_Definition t_abstract grade_abstract
Concrete, practical examples	sequence_illustration_before_fundamental t_Illustration + t_Example, h_Illustration + h_Example t_concrete, h_concrete grade_concrete
Serial	n_nextButton n_skippedLO_temp, n_skippedLO_perm grade_details
Holistic	n_prevButton, n_outline, n_jump, t_outline n_returns_LO, n_skippedLO_temp t_Introduction, t_Objectives, t_AdditionalInfo, t_Remark h_Introduction, h_Objectives, h_AdditionalInfo, h_Remark grade_overview, grade_connections sequence_exercise_last
Active experimentation	sequence_interactivity_before_fundamental sequence_interactivity_before_illustration t_Interactivity (t_Exercise + t_Exploration) h_Interactivity (h_Exercise + h_Exploration)
Reflective observation	sequence_fundamental_before_interactivity sequence_illustration_before_interactivity

	$t_notInteractivity (t_Fundamental + t_Illustration)$
Careful with details	$t_test, n_revisions_test$ $grade_details$ $t_Details (t_Remark + t_Demonstration + t_AdditionalInfo)$ $h_Details (h_Remark + h_Demonstration + h_AdditionalInfo)$
Not careful with details	$n_revisions_test$ $grade_details$
Deductive reasoning	$sequence_fundamental_before_illustration$ $sequence_abstract_first$ $grade_directApplication$
Inductive reasoning	$sequence_concrete_first$ $sequence_illustration_before_fundamental$ $grade_generalizations$
High persistence	t_total $n_testRetakes, n_returnsLO$
Low persistence	$n_testRetakes, n_hints$ $n_returnsLO$
Introversion	n_chat_msg, n_chat_login $n_forum_login, n_forum_msg, n_forum_reads$
Extraversion	n_chat_msg, n_chat_login $n_forum_login, n_forum_msg, n_forum_reads$

Table 4.2. Associations between ULSM learning preferences and behavioral patterns

As could be seen in Table 4.2, we aggregated some related behavioral indicators, yielding new relevant patterns. We thus performed groupings on the instructional type of the LO, considering for example $t_Exercise$ and $t_Exploration$ to obtain $t_Interactivity$, which can be regarded as an indicator of an *Active experimentation* learning preference. Similarly, we grouped t_Image and t_Video as representative of a *Visual* preference.

The correlations we introduced above are only based on the intensional definitions of the ULSM, as provided in Chapter 3. What we want to do is prove these correlations and perhaps reveal some new ones. This is why we performed two experimental studies to test our assumptions. The settings and results of the first experiment are presented in the next section.

4.2.2. Exploratory Study

Experiment Settings

In order to experimentally investigate the behavior of students with different learning styles in an EHS, we first performed an exploratory study involving 22 students (Popescu et al., 2008b, c). As test platform we used WELSA educational system and a course module in the area of Artificial Intelligence. Further details regarding the platform and the AI course can be found in Chapter 6.

The course module deals with search strategies and solving problems by search and is based on the fourth chapter of Poole, Mackworth and Goebel's AI textbook (Poole et al., 1998). The course consists of 4 sections and 9 subsections, including a total of 46 learning objects (LO). From the point of view of the media type, the course includes both 'Text' LOs (35), as well as 'Image', 'Video' and 'Animation' LOs (11). From the point of view of the instructional role of the LO, the course consists of 12 'Fundamental' LOs (5 'Definition' and 7 'Algorithm') and 34 'Auxiliary' LOs (4 'Additional Info', 1 'Demonstration', 14 'Example', 5 'Exercise', 3 'Exploration', 5 'Introduction', 1 'Objectives' and 1 'Remark'). The course also includes access to two communication tools, one synchronous (*chat*) and one asynchronous (*forum*) and offers two navigation choices – either by means of the *Next* and *Previous* buttons, or by means of the *Outline*.

The experiment involved 22 undergraduate students in the field of Computer Science from the University of Craiova, Romania. The experiment lasted for 4 hours: 2 hours were reserved for course studying and 2 hours for discussions and filling-in some questionnaires. For the first part of the experiment, the students accessed WELSA and all of their interactions with the system were recorded. Afterwards, the students were asked to self-assess their ULSM learning preferences, using a dedicated questionnaire. The questionnaire contains one item for each ULSM dimension, for which the student can state her/his preference as mild, moderate or strong, after being provided with a short description of it.

The next step in our study was to analyze the logs of the students, trying to identify correlations between the learning preference and the student behavior in the system. WELSA records 18 distinct types of student actions (such as *login*, *logout*, *home*, *jump*, *nextButton*, *prevButton*, *outline*, *accessLO* etc), each with its associated time stamp. For our experiment, a total of 2366 actions were recorded by the system, with a minimum of 73 and a maximum of 162 actions per student. Of course, these raw data need to be pre-processed in order to yield some useful information. The first step is to compute the duration of each action, eliminating the erroneous values (for example, an LO access time of less than 3 seconds was considered as random or a step on the way to another LO and therefore not taken into account). Relative durations and frequencies of actions were then computed starting from these values. The whole process is automatically performed by

the WELSA Analysis tool, as described in Chapter 6. The output of the tool is the set of relevant patterns, as identified in the previous section.

Experiment Results

The results of the ULSM questionnaire are summarized in Table 4.3.

<i>Preference</i> <i>ULSM characteristic</i>	<i>Strong preference</i>	<i>Moderate preference</i>	<i>Mild preference</i>	<i>Total</i>
Visual	9	5	3	17
Verbal	1	2	2	5
Abstract concepts and generalizations	1	2	0	3
Concrete, practical examples	10	4	5	19
Serial	4	5	3	12
Holistic	3	2	5	10
Active experimentation	12	4	2	18
Reflective observation	2	1	1	4
Careful with details	8	6	2	16
Not careful with details	2	2	2	6
Deductive reasoning	2	7	2	11
Inductive reasoning	3	6	2	11
Synthetic	2	8	2	12
Analytic	3	5	2	10
High persistence	5	5	3	13
Low persistence	2	5	2	9
Concentrate on one task at a time	1	6	5	12
Alternate tasks and subjects	3	5	2	10
Individual work	4	4	2	10
Team work	6	4	2	12
Introversion	1	3	0	4
Extraversion	10	6	2	18
Collaborative	6	4	3	13
Competitive	2	2	5	9
Affectivity	3	3	3	9
Thinking	3	5	5	13
Field dependence	0	5	6	11
Field independence	1	6	4	11
Intrinsic motivation	10	5	3	18
Extrinsic motivation	1	1	2	4
Deep approach	8	12	2	22
Strategic approach	4	12	6	22
Surface approach	0	9	13	22
Resistance approach	2	2	18	22

Table 4.3. Results of the ULSM questionnaire

Due to the current settings of our experiment (the structure of the AI course and the duration of the experiment), in what follows we will only analyze data regarding the following characteristics:

- Visual preference / Verbal preference
- Abstract concepts and generalizations / Concrete, practical examples
- Serial / Holistic
- Active experimentation / Reflective observation
- Careful with details / Not careful with details
- Individual work / Team work

It should be noted that this is not a limitation, since our modeling process is not a goal in itself, but just an input for the adaptation component. While identifying all student preferences could be of interest to educational psychologists, from a pragmatic point of view, the only preferences that are useful are those that can be further used for adaptation. As we will see in Chapter 5, these preferences are just the ones selected above.

In what follows we will analyze, compare and discuss the values obtained for some of the behavioral patterns that were identified in section 4.2.1. We will first consider some characteristic students with moderate to strong ULSM preferences, for which we will plot the values of relevant patterns. While this analysis does not enable us to draw any definitive conclusions (a more thorough analysis being required to this end), it is nevertheless a very helpful step. It can effectively uncover some interesting aspects, reveal anomalies and offer some explanations that inferential statistics might fail to provide. This analysis will help us illustrate the well-known fact that students behave differently during the learning process, which in the context of a web-based educational system is reflected in a different manner of interacting with the system. More importantly, this difference can be expressed in terms of behavioral patterns, which can be identified by the system. Our next endeavor will be to prove that these differences are determined by the learning style of the student. However, in order to prove these correlations, a larger student sample is needed, which we will use in our next experiment reported in section 4.2.3.

Visual/Verbal dimension. Figure 4.1. presents the access time (in seconds) of text LOs versus image and video LOs for two students with a *Visual* and a *Verbal* preference respectively. The data confirms the Visual/Verbal intensional definition, according to which learners with a *Verbal* preference tend to spend more time on text, while learners with a *Visual* style prefer images, graphics and videos.

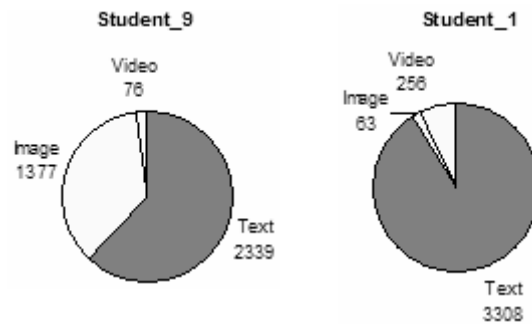


Figure 4.1. Data (number of seconds) for one student with a *Visual* preference (9) and one with a *Verbal* preference (1)

Abstract concepts and generalizations / Concrete, practical examples. Figure 4.2. presents the percentage of study time a student with an *Abstract* preference and a student with a *Concrete* preference spent on *Examples* and *Explanations* on one hand and *Definitions* and *Algorithms* on the other. The data is in agreement with the intensional definition of Abstract / Concrete learning preference.

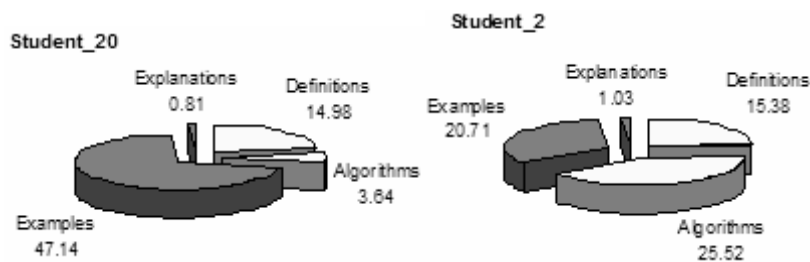


Figure 4.2. Data (percentage of study time) for one *Concrete* student (20) and one *Abstract* student (2)

Serial/Holistic dimension. Figure 4.3. presents data regarding the navigation actions of two students with a *Serial* preference and two students with a *Holistic* preference. According to the ULSM description, *Serial* learners tend to access the material in a linear way (e.g. by using the "Next" button), while *Holistic* learners prefer to jump between pages and visit the course outline frequently, in order to get the big picture. As we can see, Student_12 had a completely linear path, visiting the 9 pages of the course in the exact order. Student_5 also followed a linear path, with only 2 non-sequential steps. Both students characterized themselves as having a *Serial* preference in the ULSM questionnaire. As for the *Holistic* students (13 and 17), we can see that the number of uses of "Next" button is lower than the number of jumps between pages. However, for Student_13 we notice that the number of uses of "Next" button is very high. When we correlate this finding with the also very high number of uses of the "Previous" button, we can conclude that Student_13 jumped a lot through the course (which is in agreement

with the *Holistic* description); however, she/he did not use the dedicated Outline for this purpose but instead preferred to get to the desired page by repeatedly clicking the "Next" and "Previous" buttons.

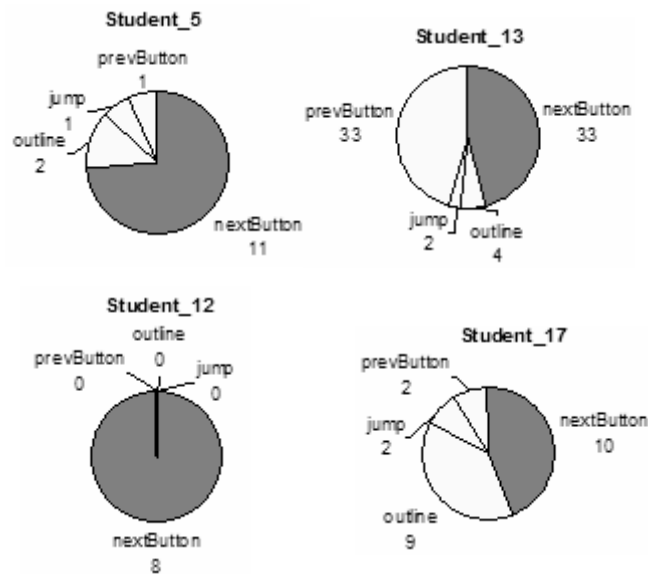
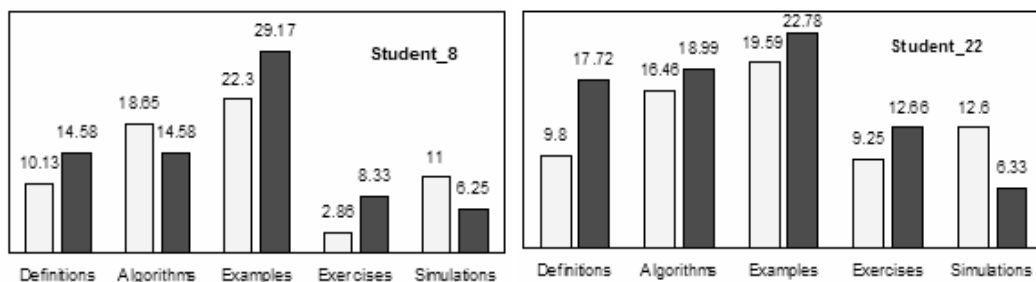


Figure 4.3. Data (number of navigation actions) for two *Serial* students (5 and 12) and two *Holistic* students (13 and 17)

Active experimentation / Reflective observation dimension. Figure 4.4. presents data about the relative time and number of LO accesses ($t_InstructionalType_rel$, $h_InstructionalType_rel$) of two students with preference towards *Active experimentation* and two students with preference towards *Reflective observation*. According to the ULSM description, *Active* learners are more attracted by actively working with the educational material and therefore spend more time and access more frequently interactive learning objects, such as *Exercises* or *Simulations*, which enable them to try things out. On the contrary, *Reflective* students prefer *Definitions*, *Algorithms* and *Examples*, which let them think more about the subject and reflect on the solutions given by others. The recorded data seem to be in agreement with these claims.



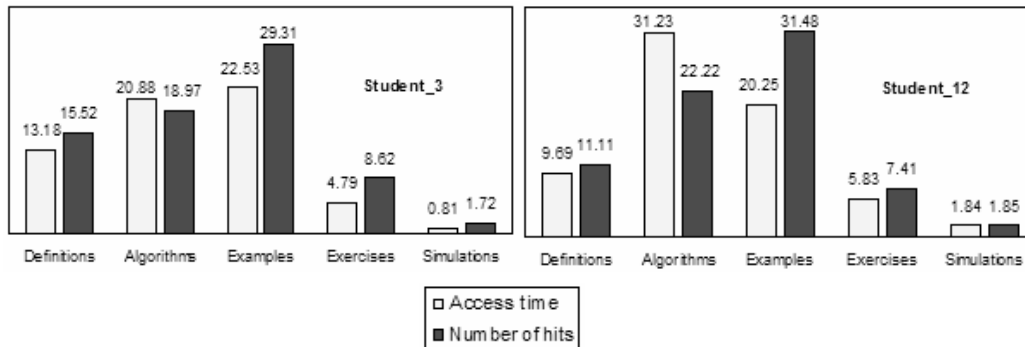


Figure 4.4. Data (percentage of study time / number of accesses) for two *Active* students (8 and 22) and two *Reflective* students (3 and 12)

Careful / Not careful with details. Figure 4.5 comparatively presents the amount of time two students spent on learning resources including details (demonstrations, remarks and additional information). Student_9, who declared herself as *Careful with details*, spent a higher amount of time on these resources as compared with Student_11, who declared herself *Not careful with details*. Consequently Student_9 obtained a higher grade on the detail-based items in the knowledge assessment test. The data is in agreement with the intensional definition of *Careful / Not careful with details* ULSM learning preference.

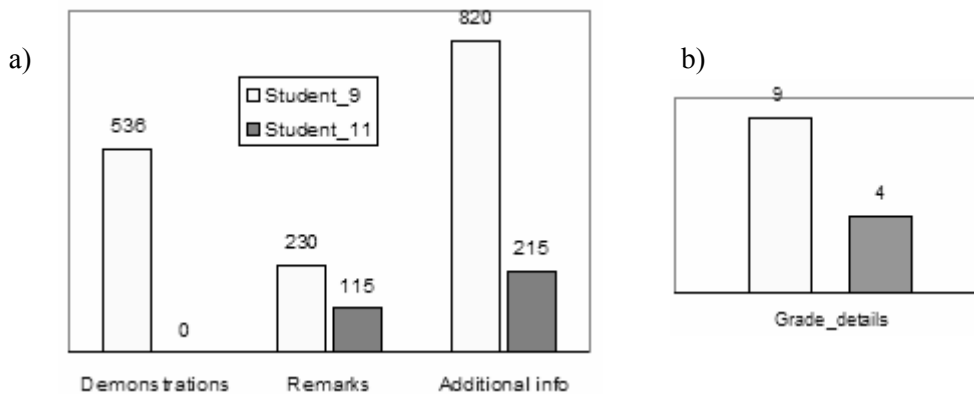


Figure 4.5. Data for one student *Careful with details* (9) and one *Not careful with details* (11): a) Number of seconds spent on demonstrations, remarks, additional info; b) Grade obtained on detail-related test questions

Individual work / Team work. Figure 4.6 illustrates the level of activity registered in chat for two students: one with a preference towards *Individual work* (Student_14) and the other who prefers *Team work* (Student_20). Student_14 did not access the chat at all (and consequently wrote no messages). Student_20 spent almost 11 minutes in chat, writing 30 messages. While this difference is in agreement with the students' characteristics, we should however note the rather limited amount of time spent in chat by

Student_20. This is a characteristic of most of the students who participated in the experiment and it is due to the fact that the course did not promote collaborative work, either by means of group assignments or the provision of more sophisticated collaborative tools.

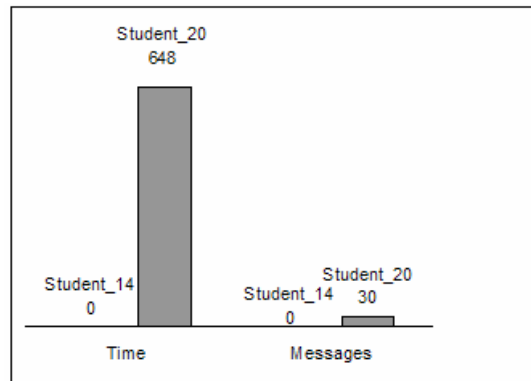


Figure 4.6. Data (time spent in chat and number of written messages) for one student with *Individual work* preference (14) and one with *Team work* preference (20)

In this section we analyzed some of the patterns of behavior exhibited by the students in an educational hypermedia system (WELSA) and put them in relation to a particular learning preference of the student. The preliminary results that we reported seem to be in agreement with the intentional definitions of the ULSM dimensions, as provided in Chapter 3. However, a larger student sample as well as a more in-depth analysis of the data is required in order to confirm our findings, which is the subject of the next section.

4.2.3. Main Study

In order to thoroughly investigate the relations between the students' patterns of behavior and their learning preferences, we repeated the experiment with a larger number of students. This time the study involved 75 undergraduate students in the field of Computer Science from the University of Craiova, Romania. The experiment lasted for 4 hours: 2 hours were reserved for course studying and 2 hours for discussions and filling-in some questionnaires. For the first part of the experiment, the students accessed WELSA and all of their interactions with the system were recorded. Afterwards, the students were asked to fill in the ULSM questionnaire, as well as to comment on their learning preferences, the structure and presentation of the course and their experience in interacting with WELSA. The latter findings will be reported in Chapter 5 and 6 respectively; in what follows we will analyze the relation between the students' self-diagnosis of the learning preferences and the patterns of behavior recorded by the system.

The results to the ULSM questionnaire are summarized in Table 4.4.

<i>Preference</i> <i>ULSM characteristic</i>	<i>Strong preference</i>	<i>Moderate preference</i>	<i>Mild preference</i>	<i>Total</i>
Visual	36	16	10	62
Verbal	4	7	2	13
Abstract concepts and generalizations	2	3	3	8
Concrete, practical examples	50	14	3	67
Serial	20	12	3	35
Holistic	12	24	4	40
Active experimentation	46	12	5	63
Reflective observation	4	4	4	12
Careful with details	30	24	6	60
Not careful with details	4	7	4	15
Individual work	15	11	7	33
Team work	20	13	9	42

Table 4.4. Results of the ULSM questionnaire

The next step in our study was to analyze the recorded data of the students. After a preliminary analysis of the system logs we discarded data from 4 students, who did not actually follow the course (2 of them were logged out from the system because of prolonged inactivity and did not log in again and 2 of them spent all the time on chat). A total of 9467 student actions were recorded by the system, with a minimum of 76 and a maximum of 212 actions per student. These raw data were then pre-processed by the Analysis tool, in order to yield useful information, as described in Chapter 6.

Next we applied statistical analysis tests to identify significant differences in the patterns of behavior exhibited by students with different ULSM preferences. To this end, we divided the students in two groups, with regard to each of the opposite ULSM preferences and we applied two-tailed t-test or two-tailed u-test on the two groups, depending on the distribution normality (which was checked with the Kolmogorov-Smirnov test). The tests were applied using SPSS software package (SPSS, 2008). The results are presented in Table 4.5, including only the values for which we obtained statistical significance ($p < 0.05$). t, u and p values are included, as well as the group for which higher values of the patterns were recorded (H).

<i>Learning preference</i>	<i>Pattern</i>
Visual / Verbal	t_Image (u = 193.00, p = 0.014, Visual → H) t_Image + t_Video (u=174.00, p=0.006, Visual → H) h_Image (u=206.00, p=0.023, Visual → H) h_Image + h_Video (u=220.00, p=0.040, Visual → H) t_Text (u = 198.00, p = 0.017, Verbal → H) t_Example (u = 213.00, p = 0.031, Visual → H)
Abstract / Concrete	t_Fundamental (u=123.00, p=0.019, Abstract → H) t_Definition (u=130.00, p=0.027, Abstract → H) t_Example (u=70.00, p=0.001, Concrete → H) h_Definition (u=139.00, p=0.040, Abstract → H) h_Example (u=124.00, p=0.020, Concrete → H) t_Image (u=94.00, p=0.004, Concrete → H) grade_abstract (u=142.00, p=0.045, Abstract → H) grade_concrete (u=143.00, p=0.047, Concrete → H)
Serial / Holistic	n_nextButton (t=2.87, p=0.005, Serial → H) n_outline (t=-4.02, p=0.000, Holistic → H) n_jump (t=-3.04, p=0.003, Holistic → H) t_AdditionalInfo (t=-2.46, p=0.016, Holistic → H) n_returns_LO (t=-3.08, p=0.003, Holistic → H) t_Exercise (t=2.31, p=0.024, Serial → H)
Active experimentation / Reflective observation	t_time (u=173.00, p=0.013, Reflective → H) t_Interactivity (t=2.24, p=0.028, Active → H) h_Interactivity (u=199.00, p=0.037, Active → H)
Careful with details / Not careful with details	t_Details (t=2.21, p=0.030, Careful → H) h_Details (u=262.00, p=0.048, Careful → H) t_Fundamental (t=2.93, p=0.005, Careful → H) n_outline (t=-2.61, p=0.019, Not careful → H) grade_details (u=181.00, p=0.002, Careful → H)
Individual work / Team work	n_chat_msg (t=-2.18, p=0.034, Team → H) t_chat (t=-2.08, p=0.043, Team → H)

Table 4.5. Behavioral patterns for which statistically significant differences were found between the two student groups

According to the results obtained for the Visual / Verbal dimension, a higher amount of time spent on image and video resources, as well as a higher number of accesses to those resources is significant for a Visual preference. Similarly, a high volume of time spent on text resources is significant for a Verbal preference. These findings are

in agreement with the intensional definition of the Visual / Verbal dimension. Furthermore, Visual students were found to spend more time on examples than Verbal students. This could be explained by the fact that a large part of the examples included in the course were in graphical format (either images or videos).

Regarding the Abstract / Concrete dimension, results show that learners with an Abstract preference accessed more frequently and spent significantly more time on definitions and fundamental resources, while learners with a Concrete preference preferred examples. Another behavior that was found to be significant for the Concrete preference is the high amount of time spent on images. Again this can be explained by the fact that most of the images included in the course were used for illustrating and exemplifying fundamental concepts. Moreover, Concrete students performed significantly better on evaluation items dealing with practical aspects, while Abstract students obtained higher grades on theoretical items.

As far as the Serial / Holistic dimension is concerned, several navigation actions were found to be significant: the use of the Next button was higher in case of Serial students, while Holistic learners prefer to jump through the pages by means of the outline. Holistic learners also tended to return more often to already visited resources, as well as spend more time on additional information. Serial students on the other hand spent more time on exercises. This can be explained by the fact that exercises were placed at the end of each section, which was convenient for serial learners but less convenient for the holistic learners, who didn't have an overall idea of the course yet.

The behavioral patterns that were found to be significant for the Active experimentation / Reflective observation dimension are the amount of time and the number of accesses to interactive resources (higher in case of students with an Active experimentation preference). The overall amount of study time was also significantly higher in case of learners with Reflective observation preference; this can be explained by the more patient nature of these students, as compared with the impulsive, "jump right in" nature of the Active students.

Students who declared to be more careful with details indeed spent significantly more time on remarks, demonstrations, additional information as well as fundamental resources as compared to the less careful ones. Additionally, they obtained better grades on items requiring a high level of detail. Students who are less careful with details visited the outline more often – this could be explained by their tendency to skip some parts of the course, which purportedly included too many details.

Finally, students who prefer to work in teams spent a longer time in chat, posting also more messages than their more individually-oriented peers.

A few more comments are in order: no significant results were found regarding the order of accessing the results. When later questioned about this behavior, the vast majority of the students (88.73%) explained that they chose to access resources in the given order, since they considered they should follow the order suggested by the teacher.

Further comments and explanations regarding this behavior are included in Chapter 5. It should also be noted that, due to the constraints of the experiment (i.e. only one 2 hours session), the learners had neither the time nor the incentive to use the provided forum. However, significant results regarding forum usage might be obtained in a different context (e.g. a longer experiment, fostering collaboration between students).

This analysis showed that students with different ULSM preferences indeed behave differently in an EHS, emphasizing also some relations between these preferences and students' behavioral patterns. Based on these results, as well as the findings from the literature, in the next section we will identify some rules for learner modeling and use them to actually diagnose students' ULSM preferences.

4.3. Automatic Identification of Student Learning Style

4.3.1. Proposed Modeling Method

Definitions and Notations

Formally, let L be a learner and let $Pref(L)$ be the set of learning preferences that characterize learner L . In the context of our work, $Pref(L) \subset Pref_{ULSM}$, where $Pref_{ULSM}$ is the set of learning preferences included in our ULSM. Specifically, $Pref_{ULSM} = \{p_visual, p_verbal, p_fieldDependence, p_fieldIndependence, p_abstract, p_concrete, p_serial, p_holistic, p_activeExperimentation, p_reflectiveObservation, p_carefulDetails, p_notCarefulDetails, p_deductive, p_inductive, p_synthesis, p_analysis, p_intrinsic, p_extrinsic, p_deep, p_strategic, p_surface, p_resistant, p_highPersistence, p_lowPersistence, p_oneTask, p_alternateTasks, p_individual, p_team, p_extraversion, p_introversion, p_competitive, p_collaborative, p_affectivity, p_thinking\}$ (meaning of each preference obviously results from its name).

The objective of this section is to conceive an implicit method for diagnosing this set of learning preferences as accurately as possible. An explicit method has already been introduced, in the form of the ULSM questionnaire. Let us denote $Pref_Q(L)$ the set of learning preferences identified by means of the student's self-diagnosis. Ideally, $Pref_Q(L) = Pref(L)$; however, due to the reasons outlined in section 4.1 (i.e. students' lack of awareness regarding their learning style, their lack of interest in filling out the questionnaire etc), this is not always the case. Since we need an as good as possible approximation of students' learning preferences that we can use as a reference model, we have adjusted the results of the questionnaire with findings from interviews conducted with the students and from teachers' own observations about the learning preferences of the students. In what follows, we will denote this set of learning preferences as $Pref_{QA}(L)$.

As we have already stated in the previous sections, our goal is to identify the learning preferences of the students by analyzing their behavioral indicators. Let us denote $Pref_B(L)$ the set of implicitly diagnosed learning preferences.

As we have already mentioned in section 4.2., in what follows we will consider a subset of $Pref_ULSM$, which can be identified from our WELSA system and can be subsequently used for adaptation, i.e. $Pref_ULSM' = \{p_visual, p_verbal, p_abstract, p_concrete, p_serial, p_holistic, p_activeExperimentation, p_reflectiveObservation, p_carefulDetails, p_notCarefulDetails, p_individual, p_team\}$. It should be noted that the preferences in $Pref_ULSM'$ are grouped on several dimensions, each with two opposite axes: $p_visual \leftrightarrow p_verbal$; $p_abstract \leftrightarrow p_concrete$ etc. $Dim_ULSM' = \{p_visual / p_verbal, p_abstract / p_concrete, p_serial / p_holistic, p_activeExperimentation / p_reflectiveObservation, p_carefulDetails / p_notCarefulDetails, p_individual / p_team\}$. Thus a student can only exhibit one of the two opposite preferences, e.g. if $p_visual \in Pref(L)$ then $p_verbal \notin Pref(L)$.

Furthermore, the student can have a level of intensity associated to each preference (either mild, moderate or strong preference). Thus for each dimension $C / \tilde{C} \in Dim_ULSM'$ we can have $Val_{C/\tilde{C}} \in \{-3, -2, -1, 1, 2, 3\}$, where positive values imply a preference towards the C axis and negative values imply a preference towards the \tilde{C} axis; the greater the absolute value, the more intense the preference (i.e. ± 3 represents a strong preference, ± 2 represents a moderate preference and ± 1 represents a mild preference). Each learner's preferences can thus be represented as a set of tuples (*Dimension, Value*):

$$PS(L) = \{(Dim_i, Val_i), \text{ where } Dim_i \in Dim_ULSM' \text{ and } Val_i \in \{-3, -2, -1, 1, 2, 3\}\}.$$

We can define $PS_{QA}(L)$ as the set of preferences with associated strengths, as identified by means of the ULSM questionnaire, combined with the findings from the interviews and researcher's observations, as above. Similarly, we can define also $PS_B(L)$ as the set of learning preferences of the students identified from their behavior in the system. It should be noted that in case of $PS_{QA}(L)$ and $PS_B(L)$, the values that can be taken by each dimension include an additional value (let us denote it "0"), which represents the lack of data regarding that particular dimension (i.e. no response in the questionnaire in case of $PS_{QA}(L)$ and no behavioral indicators available in the system in case of $PS_B(L)$).

The goal of this section is to conceive a method for identifying $Pref_B(L)$. The first step is to associate relevant behavioral patterns to each of the ULSM' preferences.

Associating Relevant Patterns to ULSM' Dimensions

In Table 4.1 we have an informal specification of the patterns that can be indicative of a particular ULSM preference, e.g. "High amount of time spent on contents with graphics, images, video", "High performance in questions related to graphics" etc. On the other hand, the data collected from the system logs are in a precise quantitative form, e.g. $t_Image = 2350s$ (the amount of time, in seconds, spent on LOs of type

"image") or $t_Image_rel = 12.5\%$ (the percentage of time spent on images versus the whole study time); $grade_image = 8.5$ (the average grade obtained on questions related to graphics). We therefore encode the values that can be taken by the patterns in three categories: *High (H)*, *Medium (M)*, *Low (L)*. Consequently, for each of the patterns we need to establish a mapping from the set of values that can be taken by the pattern to the set $\{H, M, L\}$. One way to specify this mapping is by means of the thresholds $L \leftrightarrow M$ and $M \leftrightarrow H$. Table 4.6 includes some common values for these thresholds, based on the recommendations in the literature (Graf, 2007; Garcia et al., 2007; Rovai and Barnum, 2003), as well as our experience.

Pattern	Description	L ↔ M	M ↔ H
t_mediaType t_instrType	the relative time spent by the student on LOs of type mediaType / instructionalType versus the relative average time spent on LOs of type mediaType / instructionalType (the average time is computed based on an average study time indicated by the course creator for each component LO) $t_mediaType_rel / \left(\frac{t_average_mediaType}{t_average_total_LO} \right) * 100$ $t_instrType_rel / \left(\frac{t_average_instrType}{t_average_total_LO} \right) * 100$	<75%	>125%
h_mediaType h_instrType	the relative number of visits of LOs of type mediaType versus the total relative number of LOs of type mediaType available in the course $h_mediaType_rel / \left(\frac{n_LO_mediaType}{n_LO_total} \right) * 100$ $h_instrType_rel / \left(\frac{n_LO_instrType}{n_LO_total} \right) * 100$	<75%	>125%
grade_X	the grade obtained by the student on items of type X versus the total average grade of the student $\frac{grade_X}{grade_average} * 100$	<75%	>125%
t_test	the time spent on a test versus the maximum time allowed for that test $\frac{t_test}{t_test_max} * 100$	<70%	>90%

n_revisions_test	the number of revisions made before submitting a test versus the total number of answers $\frac{n_revisions_test}{n_total_answers} * 100$	<20%	>50%
sequence_X_before_Y	the number of accesses of LOs in the order X – Y versus the number of accesses of LOs in the order Y – X. $\frac{sequence_X_before_Y}{sequence_Y_before_X} * 100$	<80%	>120%
n_nextButton	the number of "Next" button clicks versus the total number of navigation actions $\frac{n_nextButton}{n_nextButton + n_prevButton + n_jump} * 100$	<30%	>70%
n_prevButton	the number of "Previous" button clicks versus the total number of navigation actions $\frac{n_prevButton}{n_nextButton + n_prevButton + n_jump} * 100$	<30%	>70%
n_jump	the number of jump actions versus the total number of navigation actions $\frac{n_jump}{n_nextButton + n_prevButton + n_jump} * 100$	<30%	>70%
n_outline	the number of visits to "Outline" versus the total number of visited LOs $\frac{n_outline}{n_LO} * 100$	<5%	>15%
t_outline	the time spent on "Outline" versus the total time spent on the course $\frac{t_outline}{t_total} * 100$	<1%	>5%
n_skippedLO_temp	the number of LOs skipped on a temporary basis versus the total number of visited LOs $\frac{n_skippedLO_temp}{n_LO} * 100$	<5%	>15%
n_skippedLO_perm	the number of LOs skipped on a permanent basis versus the total number of visited LOs $\frac{n_skippedLO_perm}{n_LO} * 100$	<5%	>15%
n_returns_LO	the number of returns to LOs versus the total number of visited LOs	<5%	>15%

	$\frac{n_returns_LO}{n_LO} * 100$		
t_chat	the time spent on chat versus the total time spent on the course $\frac{t_chat}{t_total} * 100$	<5%	>15%
n_chat_msg	the number of messages sent on chat per course session $\frac{n_chat_msg}{n_sessions}$	<10	>30
t_forum	the time spent on forum versus the total time spent on the course $\frac{t_forum}{t_total} * 100$	<5%	>15%
n_forum_msg	the number of messages posted on forum per course session $\frac{n_forum_msg}{n_sessions}$	<1	>5
n_forum_read	the number of messages read on forum per course session $\frac{n_forum_read}{n_sessions}$	<2	>10
n_askPeerHelp n_offerPeerHelp	the number of times a student asks for / offers peer help per course session $\frac{n_askPeerHelp}{n_sessions}$ $\frac{n_offerPeerHelp}{n_sessions}$	<2	>4
n_individualAssignment	the relative number of individual assignments chosen versus the relative number of group assignments chosen $\frac{n_individualAssignments}{n_total_individualAssignments}$ $/ \frac{n_groupAssignments}{n_total_groupAssignments} * 100$	<80%	>120%

Table 4.6. Description and values for pattern thresholds

It should be noted that the values of these thresholds depend to a certain extent on the structure and the subject of the course. The above values are some general indications that are based on our experience as well as similar research findings. However, the

teacher should have the possibility to adjust these values to correspond to the particularities of her/his course. This is why our Analysis tool has a Configuration option, which allows the teacher to modify the threshold values (as detailed in Chapter 6).

We can now associate the values of the patterns with ULSM' characteristics that they are indicative of. Since the ULSM' characteristics come in opposite pairs, if an *H* value for a pattern *P* can be associated with a characteristic *C*, then an *L* value of pattern *P* can be associated with characteristic \tilde{C} (for all dimensions $C / \tilde{C} \in Dim_ULSM'$). Therefore in Table 4.7 we only include the values of the patterns that are characteristic for the left hand side axis of each ULSM' dimension. Furthermore, for each pattern we can associate a weight, indicating the relevance (the level of influence) it has on identifying a learning preference. The weight of each pattern is also included in Table 4.7, denoted by *hW* (high weight), *mW* (medium weight) and *lW* (low weight).

<i>ULSM dimension</i>	<i>Patterns</i>
p_visual / p_verbal	t_Image (H) - hW t_Video (H) - hW t_Text (L) - hW t_Sound (L) - hW h_Image (H) - mW h_Video (H) - mW h_Text (L) - mW h_Sound (L) - mW grade_Image (H) - mW n_chat_msg (L) - lW t_chat (L) - lW n_forum_msg (L) - lW n_forum_reads (L) - lW t_forum (L) - lW
p_abstract / p_concrete	sequence_fundamental_before_illustration (H) – hW sequence_abstract_first (H) – hW t_Fundamental (H) - hW t_abstract (H) – hW t_Illustration (L) – hW t_concrete (L) – hW h_Fundamental (H) – lW h_Illustration (L) - lW h_abstract (H) – lW h_concrete (L) - lW grade_abstract (H) – lW grade_concrete (L) - lW
p_serial / p_holistic	n_nextButton (H) – hW n_prevButton (L) – hW n_outline (L) – hW t_outline (L) – mW n_jump (L) - hW t_Introduction (L) – lW t_Objectives (L) – lW t_AdditionalInfo (L) - lW h_Introduction (L) – mW

	h_Objectives (L) – mW h_AdditionalInfo (L) – mW n_skippedLO_temp (L) – hW n_skippedLO_perm (L) – mW n_returns_LO (L) - mW grade_details (H) – lW grade_overview (L) – lW grade_connections (L) – lW sequence_exercise_last (L) - lW
p_activeExperimentation / p_reflectiveObservation	sequence_interactivity_before_fundamental (H) - hW sequence_interactivity_before_illustration (H) – hW t_Exercise (H) - mW t_Exploration (H) - hW h_Exercise (H) - lW h_Exploration (H) - lW
p_carefulDetails / p_notCarefulDetails	t_test (H) - hW n_revisions_test (H) - hW grade_details (H) - mW t_Details (t_Remark + t_Demonstration + t_AdditionalInfo) (H) – mW h_Details (h_Remark + h_Demonstration + h_AdditionalInfo) (H) - lW
p_individual / p_team	n_chat_msg (L) – hW t_chat (L) – hW n_forum_msg (L) – hW n_forum_reads (L) – hW t_forum (L) – hW n_individualAssignment (H) – hW n_askPeerHelp (L) – mW n_offerPeerHelp (L) - mW

Table 4.7. Relevant patterns for each ULSM dimension, together with associated weights (*L/H* – Low / High value of the pattern; *hW, mW, lW* – high / medium / low weight of the pattern)

A few notes should be made regarding the above table: the number of visits (hits) to an educational resource was found to be less indicative of the student’s preference than the time spent on that particular resource (as revealed by the statistical analysis in section 4.2); consequently, *t_LO* was assigned a higher weight than *h_LO*. The grades obtained by students were generally allocated lower weights in defining their learning preferences since it can be argued that students’ performance depends largely on other factors, such as their motivation; thus a student may obtain a good grade on an item that doesn’t correspond to her preferences, in case the student was motivated enough to prepare her for that task. It can also be noted that there are some patterns which are associated to several ULSM’ preferences; an example is the level of activity students have in communication channels (chat and forum), which is mainly indicative of a *Team work* preference but could also be associated, to a certain extent, with a *Verbal* preference.

As in the case of thresholds, the above associations and weights are merely general recommendations; the importance of each of the patterns may change with the specificities of the course. For example, in case of a course which contains a very small number of group assignments that the students may choose from, the *n_individualAssignment* pattern is not very relevant anymore and should be assigned a lower weight. Also, some patterns may not be applicable for some courses, in case the course does not include that particular feature. In this case, the teacher should have the possibility to eliminate some of the patterns, which are not relevant for her/his course. Our Analysis tool has been conceived to accommodate all these requirements, offering the teacher the possibility to adjust the patterns' weights and thresholds (as presented in Chapter 6).

The values for the patterns are computed from the student actions, as recorded by the system. Obviously, the larger the number of available actions, the more reliable the resulted pattern. Therefore our method (and consequently our Analysis tool) weights the value of each pattern with a reliability coefficient, which is computed from the number of corresponding actions in the system log. Hence a pattern can have a high reliability degree (*hR*), a medium reliability degree (*mR*) or a low reliability degree (*lR*). Thus the particularities of the course are reflected in the patterns' weights, while the particularities of the student interaction with the system are reflected in the patterns' reliability values.

Computing the Learner Preference

For each characteristic $C \in ULSM'$, we have a set of relevant patterns P_1, P_2, \dots, P_n , each with its weight W_1, W_2, \dots, W_n , $P_i \in \{H, M, L\}$, $W_i \in \{hW, mW, lW\}$ (as in Table 4.7). As already mentioned, if an *H* value for a pattern P_i can be associated with a characteristic C , then an *L* value of pattern P_i can be associated with the opposite characteristic \tilde{C} .

For each student, we can determine the values corresponding to all the patterns for each of the characteristics in $ULSM'$, together with the reliability level of these values. Thus for characteristic C and for student j we have: the pattern values P_i^j with the weights W_i (the weights are the same for all students) and the reliability levels R_i^j , with $P_i^j \in \{H, M, L\}$, $W_i \in \{hW, mW, lW\}$, $R_i^j \in \{hR, mR, lR\}$, where the weights and reliability levels are subunitary values (i.e. $hW, mW, lW, hR, mR, lR \in [0,1]$). We can now compute the value of student j preference for characteristic C with the following formula:

$$V_j(C) = \frac{\sum_{i=1}^n p_i^j * R_i^j * W_i}{n}, \quad \text{where } p_i^j = \begin{cases} 1 & \text{if } P_i^j = P_i \\ 0 & \text{if } P_i^j = M \\ -1 & \text{otherwise} \end{cases}$$

The value obtained for $V_j(C)$ can be interpreted as follows: if $V_j(C) > 0$ then we can say that student j has a preference towards characteristic C ; if $V_j(C) < 0$ then we can say that student j has a preference towards the opposite characteristic, \tilde{C} . Furthermore, the absolute value of $V_j(C)$ gives an indication on the strength of the preference: a value close to 0 implies a mild preference (a rather balanced learning style), while greater values imply stronger preferences.

A few more comments on this formula are in order. First it should be noted that

$V_j(C) \in \left[-\frac{\sum_{i=1}^n W_i}{n}, \frac{\sum_{i=1}^n W_i}{n}\right] \subseteq [-1,1]$, for $\forall j$. The maximum value for $V_j(C)$ is obtained when all the patterns have values indicating towards the characteristic C (i.e. $p_i^j = 1, \forall i = 1..n$) and there is enough data available for student j to reliably compute all the patterns P_i^j (i.e. $R_i^j = 1, \forall i = 1..n$). Similarly, the minimum value for $V_j(C)$ is obtained when all the patterns have values indicating towards the characteristic \tilde{C} (i.e. $p_i^j = -1, \forall i = 1..n$) and there is enough data available for student j to reliably compute all the patterns P_i^j (i.e. $R_i^j = 1, \forall i = 1..n$). When we don't have enough information to compute a reliable value for pattern P_i^j , we want that value to contribute less to the final diagnosis; when we have very few data on a student, most R_i^j will be very small and consequently $V_j(C)$ will be close to 0, indicating a balanced learning style. Indeed, when lacking data to make an informed diagnosis, a balanced preference is the safest assumption one can make.

We can also compute a confidence value associated to each $V_j(C)$, reflecting the degree of trust that we can have in the value of the student j 's preference for characteristic C (based on the availability of data for student j):

$$Conf_j(C) = \frac{\sum_{i=1}^n R_i^j}{n}$$

It should be noted that $Conf_j(C) \in [0,1]$. A small value implies a low degree of confidence in the value $V_j(C)$, while a large value implies a high degree of confidence.

The above method was implemented in an Analysis tool, which offers the following functionalities:

- configure pattern weights
- configure pattern thresholds
- compute pattern values
- compute values and confidence degree for learner preferences
- compute various statistics.

The Analysis tool is presented in detail in Chapter 6. In what follows we empirically evaluate the underlying modeling approach.

4.3.2. Experimental Validation of the Modeling Method

Experiment Settings

In order to validate the proposed rule-based modeling method, we applied it on the data collected from the 71 undergraduate students that participated in our study, as described in section 4.2.

First we modified some of the pattern weights, as well as eliminated some of the patterns which were not relevant in the context of our experiment. Table 4.8 includes the adjusted weights and patterns. Thus we have excluded the patterns *t_Sound* and *h_Sound*, since the course did not include any audio resources. Furthermore, although WELSA provides a forum, due to the temporal constraints of the experiment, the learners had neither the time nor the incentive to use the forum. We have therefore excluded the patterns related to it from our analysis (*n_forum_msg*, *n_forum_reads*, *t_forum*). Also the course did not include any online evaluation tests, so the two related patterns were also left out (*t_test*, *n_revisions_test*). Finally, there were no group/individual assignments that the students could choose from, so the patterns *n_individualAssignment*, *n_askPeerHelp*, as well as *n_offerPeerHelp* were excluded from our analysis.

The default pattern thresholds from Table 4.6 were used, since there were no inconsistencies between these values and the course structure.

<p><i>p_visual / p_verbal</i></p> <p>t_Image – hW t_Video – hW t_Text – hW h_Image – mW h_Video – mW h_Text – mW grade_Image – IW n_chat_msg – IW t_chat – IW</p>	<p><i>p_abstract / p_concrete</i></p> <p>sequence_fundamental_before_illustration – hW sequence_abstract_first – hW t_Fundamental – hW t_abstract – hW t_Illustration – hW t_concrete – hW h_Fundamental – hW h_Illustration – hW h_abstract – IW h_concrete – IW grade_abstract – IW grade_concrete – IW</p>
<p><i>p_serial / p_holistic</i></p> <p>n_nextButton – hW n_prevButton – hW n_outline – hW t_outline – mW n_jump – hW t_Introduction – IW t_Objectives – IW</p>	<p><i>p_activeExperimentation / p_reflectiveObservation</i></p> <p>sequence_interactivity_before_fundamental – hW sequence_interactivity_before_illustration – hW t_Exercise – mW t_Exploration – hW h_Exercise – IW h_Exploration – IW</p>

t_AdditionalInfo – IW h_Introduction – mW h_Objectives – mW h_AdditionalInfo – mW n_skippedLO_temp – hW n_skippedLO_perm – mW n_returns_LO – mW grade_details – IW grade_overview – IW grade_connections – IW sequence_exercise_last – IW	$p_carefulDetails / p_notCarefulDetails$ grade_details – mW t_Details (t_Remark + t_Demonstration + t_AdditionalInfo) – mW h_Details (h_Remark + h_Demonstration + h_AdditionalInfo) – IW
	$p_individual / p_team$ n_chat_msg – IW t_chat – IW

Table 4.8. Patterns and associated weights that were used in our experiment

Next we computed the patterns and then, based on them, the learner preferences and the associated confidence degrees.

Evaluation Method

In order to evaluate the quality of our method, we compare the results obtained using the rule-based modeling approach (LP_{Rule}), with the results obtained using the ULSM questionnaire (LP_{Quest}). We consider three possible values for each dimension $C / \tilde{C} \in Dim_ULSM$: strong/medium preference towards C (P_C), strong/medium preference towards \tilde{C} ($P_{\tilde{C}}$) or balanced preference (P_B).

In case of the preferences obtained by means of the ULSM questionnaire, P_C corresponds to the values $\{3, 2\}$, $P_{\tilde{C}}$ corresponds to the values $\{-3, -2\}$, while P_B corresponds to the values $\{-1, 1\}$. In case of the preferences obtained by means of the

rule-based method (i.e. $V_j(C)$), values in $[-w, w]$, with $w = \frac{\sum_{i=1}^n W_i}{n}$ had to be mapped to the 3-item scale. The range was divided in 3 equal parts: P_C corresponds to the values greater than $\frac{1}{3} * w$, $P_{\tilde{C}}$ corresponds to the values smaller than $-\frac{1}{3} * w$, while P_B corresponds to the values in $[-\frac{1}{3} * w, \frac{1}{3} * w]$.

The precision of our method can be obtained with the following formula:

$$\text{Precision} = \frac{\sum_{j=1}^M \text{Sim}(LP_{Rule}^j, LP_{Quest}^j)}{M},$$

where

$$Sim(LP_{Rule}^j, LP_{Quest}^j) = \begin{cases} 1 & \text{if } LP_{Rule}^j = LP_{Quest}^j \\ 0.5 & \text{if } LP_{Rule}^j \neq LP_{Quest}^j \text{ and } (LP_{Rule}^j = P_B \text{ or } LP_{Quest}^j = P_B) \\ 0 & \text{otherwise} \end{cases}$$

M is the number of students in the sample for which we compute the precision.

The above formula is based on the similarity between the results obtained using our rule-based method and the reference results (obtained by means of the ULSM questionnaire).

Results and Discussion

Table 4.9 presents the results that we obtained using the rule-based modeling method, for each of the ULSM dimensions.

ULSM dimension	Precision
p_visual / p_verbal	73.94%
p_abstract / p_concrete	82.39%
p_serial / p_holistic	78.17%
p_activeExperimentation / p_reflectiveObservation	84.51%
p_carefulDetails / p_notCarefulDetails	71.13%
p_individual / p_team	64.08%

Table 4.9. Precision of the rule-based modeling method

As we can see, we obtained very good results for two ULSM dimensions (p_abstract / p_concrete and p_activeExperimentation / p_reflectiveObservation), good results for three ULSM dimensions (p_visual / p_verbal, p_serial / p_holistic, p_carefulDetails / p_notCarefulDetails) and moderate results for one ULSM dimension (p_individual / p_team).

The less accurate results obtained for the p_individual / p_team dimension can be explained by the very small number of behavioral patterns used (just two patterns were relevant in the current conditions of the experiment). Furthermore, the students' use of chat was very limited, as resulted from the analysis of available data. When questioned about this aspect, the arguments given by students who declared having a preference towards team work fell in two main categories: some of them prefer "face-to-face" interaction, others said that the course did not necessitate large amount of collaboration since no group assignments existed. Further experiments including team assignments and more sophisticated collaborative tools should be performed in order to obtain better outcomes.

The very good results obtained in case of p_abstract / p_concrete and p_activeExperimentation / p_reflectiveObservation can be attributed to the relatively large number of relevant patterns, as well as to the course composition, which included plenty of related educational resources (*Examples, Exercises, Explorations* etc) and consequently led to the availability of the relevant student data. As expected, the efficiency of our method depends on the amount of data available, which is based both on the amount of time spent by students interacting with the platform and on the nature of the course and the variety of resources it is made up of.

For comparison, we include in Table 4.10 the results obtained with the approaches used in the papers (Cha et al., 2006a), (Garcia et al., 2007) and (Graf, 2007), that we have introduced in section 4.1. It can be observed that our rule-based modeling method yielded above average results.

It should be noted that in the three analyzed papers the learning style model used is Felder-Silverman and the modeling approaches are various, ranging from rule-based modeling to Bayesian networks, Decision trees and Hidden Markov models. The formula used for computing precision in case of (Garcia et al., 2007) and (Graf, 2007) is similar with the one defined above. In case of (Cha et al., 2006a), only students with moderate to strong FSLSM preferences (i.e. ILS score ≥ 5) are considered.

FSLSM dimension / Modeling Approach	Active / Reflective	Sensing / Intuitive	Visual / Verbal	Sequential / Global
(Cha et al., 2006a) – Decision Trees	66.67%	77.78%	100%	71.43%
(Cha et al., 2006a) – Hidden Markov Models	66.67%	77.78%	85.72%	85.72%
(Garcia et al., 2007) – Bayesian Networks	58%	77%	N/A	63%
(Graf, 2007) - Bayesian Networks	62.50%	65.00%	68.75%	66.25%
(Graf, 2007) – Rule based approach	79.33%	77.33%	76.67%	73.33%

Table 4.10. Precision of learner modeling methods according to FSLSM model in (Cha et al., 2006a), (Garcia et al., 2007) and (Graf, 2007)

4.4. From ULSM to Traditional Learning Style Models

One of the advantages of ULSM model is that based on it we can categorize the student in various traditional learning style models. This section illustrates this approach with three popular learning style models: Ned Herrmann's Whole Brain Model

(Herrmann, 1996), Felder-Silverman learning style model (Felder and Silverman, 1988) and Kolb learning style model (Kolb, 1999), all of which were described in more detail in Chapter 3. First the correspondence rules between ULSM and the above learning style models are presented; next the method is evaluated experimentally and the obtained results are reported.

4.4.1. Correspondence Rules between ULSM Preferences and Traditional Learning Style Models

We are now interested in categorizing the student according to a particular learning style model. Let $LS_M(L)$ be the learning style of learner L with regard to learning style model M . There are several possibilities:

1. some learning style models include the learner into only one learning style
2. others assume that a learner may exhibit strong preference for one or more categories
3. others offer several dimensions, each with two opposite axes.

In the first case, $LS_M(L)$ has exactly one element, in the second case $LS_M(L)$ may include one or more elements, depending on learner L , while in the third case, $LS_M(L)$ is an n -tuple, where n is the number of dimensions defined in the learning style model.

Let us take for example Ned Herrmann's Whole Brain Model (Herrmann, 1996), according to which the brain can be divided into four quadrants, each area having an associated model of thinking and learning:

- left cerebral – "theorists"
- left limbic – "organizers"
- right limbic – "humanitarians"
- right cerebral – "innovators".

Therefore for this model we have: $Herrmann_model_set = \{"Theorist", "Organizer", "Humanitarian", "Innovator"\}$. According to Herrmann, about 7% of the population have a strong preference in only one quadrant, 60% have strong preferences in two quadrants, 30% have strong preferences in three quadrants and 3% have strong preferences in all four quadrants (so called 'quadruple dominant' or 'whole brain' profile). This means that for a learner L , we have $LS_{Herrmann_model}(L) \subseteq Herrmann_model_set$. For example, for a particular learner L_1 we can have $LS_{Herrmann_model}(L_1) = \{"Humanitarian"\}$, while for another learner L_2 we can have $LS_{Herrmann_model}(L_2) = \{"Humanitarian", "Innovator"\}$.

The following set of four rules can be extracted from the characteristics of the four learning styles, as they are defined by Herrmann (Herrmann, 1996):

<p>THEORIST</p> <p>IF</p> <p><i>p_analysis</i> ∈ Pref(L) AND <i>p_abstract</i> ∈ Pref(L) AND <i>p_thinking</i> ∈ Pref(L) AND <i>p_introversion</i> ∈ Pref(L) AND <i>p_individual</i> ∈ Pref(L) AND <i>p_fieldIndependence</i> ∈ Pref(L) AND <i>p_reflectiveObservation</i> ∈ Pref(L) AND</p> <p>THEN</p> <p><i>LSHerrmann_model</i>(L) ∃ "Theorist"</p>	<p>INNOVATOR</p> <p>IF</p> <p><i>p_holistic</i> ∈ Pref(L) <i>p_abstract</i> ∈ Pref(L) <i>p_synthesis</i> ∈ Pref(L) AND <i>p_activeExperimentation</i> ∈ Pref(L) AND <i>p_visual</i> ∈ Pref(L) AND <i>p_inductive</i> ∈ Pref(L) AND</p> <p>THEN</p> <p><i>LSHerrmann_model</i>(L) ∃ "Innovator"</p>
<p>ORGANIZER</p> <p>IF</p> <p><i>p_carefulDetails</i> ∈ Pref(L) AND <i>p_serial</i> ∈ Pref(L) AND <i>p_concrete</i> ∈ Pref(L) AND <i>p_deductive</i> ∈ Pref(L) AND <i>p_oneTask</i> ∈ Pref(L) <i>p_highPersistence</i> ∈ Pref(L)</p> <p>THEN</p> <p><i>LSHerrmann_model</i>(L) ∃ "Organizer"</p>	<p>HUMANITARIAN</p> <p>IF</p> <p><i>p_team</i> ∈ Pref(L) AND <i>p_extraversion</i> ∈ Pref(L) AND <i>p_affectivity</i> ∈ Pref(L) AND <i>p_fieldDependence</i> ∈ Pref(L) AND <i>p_verbal</i> ∈ Pref(L) AND <i>p_concrete</i> ∈ Pref(L) AND</p> <p>THEN</p> <p><i>LSHerrmann_model</i>(L) ∃ "Humanitarian"</p>

For example, the intended interpretation of the ORGANIZER rule is: if a learner is detail oriented, has preference towards a serial, step-by-step approach (as opposed to a holistic approach), has preference of processing concrete information (rather than abstract or general information), has preference for deductive (rather than inductive) reasoning, usually concentrates on a single task at a time (rather than on multiple tasks) and has a high persistence in studying then she/he can be inferred as belonging to the "Organizer" quadrant, according to Ned Herrmann's model.

Let us now take another example, the Felder-Silverman learning style model (Felder and Silverman, 1988). According to this model learners are characterized by their preferences in four dimensions:

- active versus reflective learners
- sensing versus intuitive learners
- visual versus verbal learners
- sequential versus global learners.

Therefore for this model we have: *FelderSilverman_model_set* = {(A1, A2, A3, A4) | A1 ∈ {"Active", "Reflective"}, A2 ∈ {"Sensing", "Intuitive"}, A3 ∈ {"Visual", "Verbal"}, A4 ∈ {"Sequential", "Global"}}. This means that for all learners L, we have: *LSFelderSilverman_model*(L) ∈ *FelderSilverman_model_set*. For example, for a particular learner L₁ we might have: *LSFelderSilverman_model*(L₁) = ("Active", "Sensing", "Visual", "Global").

The following set of rules can be extracted from the characteristics of the four learning dimensions, as they are defined in (Felder and Silverman, 1988):

<p>ACTIVE IF $p_{activeExperimentation} \in Pref(L)$ AND $p_{team} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Active"$</p>	<p>SENSING IF $p_{concrete} \in Pref(L)$ AND $p_{carefulDetails} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Sensing"$</p>
<p>REFLECTIVE IF $p_{reflectiveObservation} \in Pref(L)$ AND $p_{individual} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Reflective"$</p>	<p>INTUITIVE IF $p_{abstract} \in Pref(L)$ AND $p_{notCarefulDetails} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Intuitive"$</p>
<p>VISUAL IF $p_{visual} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Visual"$</p>	<p>SEQUENTIAL IF $p_{serial} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Sequential"$</p>
<p>VERBAL IF $p_{verbal} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Verbal"$</p>	<p>GLOBAL IF $p_{holistic} \in Pref(L)$ THEN $LS_{FelderSilverman_model}(L) \ni "Global"$</p>

As we can see, in case of the "Visual"/"Verbal" and "Sequential"/"Global" dimensions, there is a one-to-one correspondence between the learning preference in $Pref_ULSM$ and the learning style axis in $LS_{FelderSilverman_model}(L)$.

Finally, let us take the example of Kolb's learning style model (Kolb, 1984), according to which there are four possible learning styles:

- Diverging (Concrete Experience / Reflective Observation)
- Assimilating (Abstract Conceptualization / Reflective Observation)
- Converging (Abstract Conceptualization / Active Experimentation)
- Accommodating (Concrete Experience / Active Experimentation).

Therefore for this model we have: $Kolb_model_set = \{"Diverging", "Converging", "Assimilating", "Accommodating"\}$. This means that for a learner L , we have $LS_{Kolb_model}(L) \in Kolb_model_set$. For example, for a particular learner L_1 we may have $LS_{Kolb_model}(L_1) = "Diverging"$.

The following set of rules can be extracted from the characteristics of the four learning styles, as they are defined in (Kolb, 1999):

<p>CONVERGING</p> <p>IF</p> <p>$p_abstract \in Pref(L)$ AND $p_activeExperimentation \in Pref(L)$ AND $p_thinking \in Pref(L)$ AND $p_deductive \in Pref(L)$ AND $p_introversion \in Pref(L)$ AND</p> <p>THEN</p> <p>$LS_{Kolb_model}(L) = "Converging"$</p>	<p>ASSIMILATING</p> <p>IF</p> <p>$p_abstract \in Pref(L)$ AND $p_reflectiveObservation \in Pref(L)$ AND $p_inductive \in Pref(L)$ AND $p_thinking \in Pref(L)$ AND $p_introversion \in Pref(L)$ AND</p> <p>THEN</p> <p>$LS_{Kolb_model}(L) = "Assimilating"$</p>
<p>DIVERGING</p> <p>IF</p> <p>$p_concrete \in Pref(L)$ AND $p_reflectiveObservation \in Pref(L)$ AND $p_affectivity \in Pref(L)$ AND $p_inductive \in Pref(L)$ AND $p_extraversion \in Pref(L)$ AND</p> <p>THEN</p> <p>$LS_{Kolb_model}(L) = "Diverging"$</p>	<p>ACCOMMODATING</p> <p>IF</p> <p>$p_concrete \in Pref(L)$ AND $p_activeExperimentation \in Pref(L)$ AND $p_deductive \in Pref(L)$ AND $p_affectivity \in Pref(L)$ AND $p_extraversion \in Pref(L)$ AND</p> <p>THEN</p> <p>$LS_{Kolb_model}(L) = "Accommodating"$</p>

4.4.2. Experimental Results

In order to test the validity of the correspondence rules introduced in the previous section we compared the results obtained by means of the ULSM versus traditional learning style questionnaires. Thus, besides the ULSM questionnaire, 3 more measuring instruments were applied to the 75 students who participated in our experiment: Herrmann Brain Dominance Instrument, Soloman and Felder Index of Learning Styles questionnaire and Kolb's Learning Style Inventory.

In order to compare the results and compute precision values, various mappings had to be performed, since the result scales provided by the 4 measuring instruments were different, as was the number of learning style preferences that could be obtained as outcome (i.e. the nature and cardinality of $LS_M(L)$).

We will start with the relatively straightforward correspondence ULSM \rightarrow FLSM. As we can see from the previous section, the rules corresponding to the two poles of a FLSM dimension are related, so we can consider in our analysis only the 4 dimensions (active / reflective, sensing / intuitive, visual / verbal, sequential / global), instead of the 8 poles. Let us denote by D_{Quest}^j the score obtained for FLSM dimension D by student j , by filling in the dedicated ILS questionnaire. $D_{Quest}^j \in \{-11, -9, -7, -5, -3, -1, 1, 3, 5, 7, 9, 11\}$. Similarly, let us denote by D_{Rule}^j the value computed for FLSM dimension D with the correspondence rules defined in the previous section.

$$D_{Rule}^j = \frac{\sum_{i=1}^n LP_i^j}{n}, \text{ where } LP_i^j \text{ represent the values filled in by student } j \text{ in the}$$

ULSM questionnaire for the n learning preferences included in the correspondence rule of dimension D . $D_{Rule}^j \in [-3, 3]$.

The precision of our method can be obtained with the following formula (for each dimension D):

$$\text{Precision} = \frac{\sum_{j=1}^M \text{Sim}(D_{Rule}^j, D_{Quest}^j)}{M},$$

where

$$\text{Sim}(D_{Rule}^j, D_{Quest}^j) = \begin{cases} 1 & \text{if } D_{Rule}^j \geq 1.5 \text{ and } D_{Quest}^j \geq 5 \text{ or} \\ & D_{Rule}^j \leq -1.5 \text{ and } D_{Quest}^j \leq -5 \text{ or} \\ & D_{Rule}^j \in (-1.5, 1.5) \text{ and } D_{Quest}^j \in \{-3, -1, 1, 3\} \\ 0 & \text{if } D_{Rule}^j \geq 1.5 \text{ and } D_{Quest}^j \leq -5 \text{ or} \\ & D_{Rule}^j \leq -1.5 \text{ and } D_{Quest}^j \geq 5 \\ 0.5 & \text{otherwise} \end{cases}$$

M is the number of students in the sample for which we compute the precision (in our case $M = 75$).

The above formula is based on the similarity between the results obtained using our correspondence rules and the reference results (obtained by means of the FLSM questionnaire).

Table 4.11 presents the results that we obtained using the correspondence rule method, for each of the FLSM dimensions.

FLSM dimension	Precision
Active / Reflective	80.67 %
Sensing / Intuitive	72.00 %
Visual / Verbal	90.67 %
Sequential / Global	77.33 %

Table 4.11. Precision of the correspondence rules for FLSM

Similarly, in what follows we will compute the precision of the correspondence ULSM \rightarrow Herrmann model. Let us denote by S_{Quest}^j the score obtained for style S (i.e. Theorist, Organizer, Innovator, Humanitarian) by student j , by means of filling in the HBDI questionnaire. $S_{Quest}^j \in [0, 30]$. Similarly, let us denote by S_{Rule}^j the value computed for the style S with the correspondence rules defined in the previous section.

$$S_{Rule}^j = \frac{\sum_{i=1}^n LP_i^j}{n}, \text{ where } LP_i^j \text{ represent the values filled in by student } j \text{ in the}$$

ULSM questionnaire for the n learning preferences included in the correspondence rule of learning style S . $S_{Rule}^j \in [-3, 3]$.

The precision of our method can be obtained with the following formula (for each learning style S):

$$\text{Precision} = \frac{\sum_{j=1}^M \text{Sim}(S_{Rule}^j, S_{Quest}^j)}{M},$$

where

$$\text{Sim}(S_{Rule}^j, S_{Quest}^j) = \begin{cases} 1 & \text{if } S_{Rule}^j \geq 1.5 \text{ and } S_{Quest}^j > 20 \text{ or} \\ & S_{Rule}^j \leq -1.5 \text{ and } S_{Quest}^j < 10 \text{ or} \\ & S_{Rule}^j \in (-1.5, 1.5) \text{ and } S_{Quest}^j \in [10, 20] \\ 0 & \text{if } S_{Rule}^j \geq 1.5 \text{ and } S_{Quest}^j < 10 \text{ or} \\ & S_{Rule}^j \leq -1.5 \text{ and } S_{Quest}^j > 20 \\ 0.5 & \text{otherwise} \end{cases}$$

M is the number of students in the sample for which we compute the precision (in our case $M = 75$).

Table 4.12 presents the results that we obtained using the correspondence rule method, for each of the four Herrmann learning styles.

Herrmann learning style	Precision
Theorist	88.67 %
Organizer	82.67 %
Innovator	79.33 %
Humanitarian	76.00 %

Table 4.12. Precision of the correspondence rules for Herrmann model

In case of the correspondence ULSM \rightarrow Kolb model, we take a slightly different mapping approach. The Kolb Learning Style Inventory yields four scores, corresponding to the students' preference towards abstract conceptualization (AC), concrete experience (CE), active experimentation (AE) and reflective observation (RO), $AC, CE, AE, RO \in [12, 48]$. By combining these results on the two axis, it can be obtained the learning style of the student (i.e. if $AC^j > CE^j$ and $AE^j > RO^j$ then student j has Converging learning style; if $AC^j < CE^j$ and $AE^j < RO^j$ then student j has Diverging learning style; if $AC^j > CE^j$ and $AE^j < RO^j$ then student j has Assimilating learning style; if

$AC^j < CE^j$ and $AE^j > RO^j$ then student j has Accommodating learning style). It can be noticed that the Converging and Diverging styles are at opposite poles, just as Assimilating and Accommodating styles are (which is reflected also in the structure of the correspondence rules). We will therefore use in our analysis the two axes: Converging / Diverging and Assimilating / Accommodating, that we will denote A_{CD} and A_{AA} respectively (much like in the case of FLSM correspondence). Let us denote by $A_{CD_Rule}^j$ the value computed for axis Converging / Diverging with the correspondence rules defined in the previous section.

$$A_{CD_Rule}^j = \frac{\sum_{i=1}^n LP_i^j}{n}, \text{ where } LP_i^j \text{ represent the values filled in by student } j \text{ in the}$$

ULSM questionnaire for the n learning preferences included in the correspondence rules of axis A_{CD} . $A_{CD_Rule}^j \in [-3, 3]$, with positive values implying a Converging learning style and negative values implying a Diverging style. Let us denote by $A_{CD_Quest}^j$ the value obtained for axis A_{CD} by student j , by means of Kolb's Inventory. $A_{CD_Quest}^j$ can be computed starting from the AC^j, CE^j, AE^j, RO^j values as follows:

$$A_{CD_Quest}^j = AC^j - CE^j + AE^j - RO^j$$

A positive value is an indication of a Converging learning style, while a negative value is an indication of a Diverging learning style.

In a similar fashion we can define $A_{AA_Rule}^j$ and $A_{AA_Quest}^j$, for the Assimilating / Accommodating axis.

$$A_{AA_Rule}^j = AC^j - CE^j + RO^j - AE^j$$

As previously, positive values imply an Assimilating learning style and negative values an Accommodating learning style, in case of both $A_{AA_Rule}^j$ and $A_{AA_Quest}^j$.

The precision of our method can be expressed in terms of similarity between the values obtained by means of the correspondence rules and the reference values (resulted from Kolb's Inventory):

$$\text{Precision} = \frac{\sum_{j=1}^M (\text{Sim}(A_{CD_Rule}^j, A_{CD_Quest}^j) + \text{Sim}(A_{AA_Rule}^j, A_{AA_Quest}^j)) / 2}{M}$$

where

$$\text{Sim}(A_{CD_Rule}^j, A_{CD_Quest}^j) = \begin{cases} 1 & \text{if } \text{sgn}(A_{CD_Rule}^j) = \text{sgn}(A_{CD_Quest}^j) \\ 0 & \text{otherwise} \end{cases}$$

$$Sim(A_{AA_Rule}^j, A_{AA_Quest}^j) = \begin{cases} 1 & \text{if } \text{sgn}(A_{AA_Rule}^j) = \text{sgn}(A_{AA_Quest}^j) \\ 0 & \text{otherwise} \end{cases}$$

M is the number of students in the sample for which we compute the precision (in our case $M = 75$).

It should be noted that the 4 learning styles of Kolb's model are interdependent, being computed on the basis of the two dimensional scores: (*AC-CE*) and (*AE-RO*). This is different from the FLSM and Herrmann model case, in which the learning styles are independent of each other. Due to this particularity, we will compute a single precision value, referring not to the accuracy of one correspondence rule (as in the previous cases) but to the accuracy of all the four correspondence rules (the method as a whole). The precision value that we obtained in our experiment using this formula is 70.67%.

Clearly, it is not possible to obtain a perfect correspondence between ULSM preferences and the traditional learning style models, due to several factors: i) the measuring instruments may not be totally reflective of students' learning preferences (due to construct validity issues); ii) students' self-diagnosis may be imprecise (due to students' low level of awareness regarding their learning preferences); iii) students may tend to choose answers arbitrarily instead of thinking carefully about them (due to lack of interest, motivation or attention); iv) the correspondence rules are intrinsically limited, due to the complexity and many nuances of the learning styles. We therefore did not expect very high accuracy levels for the proposed correspondence rules. However, the experimental results obtained are very encouraging (constantly over 70% and with an average higher than 80%), confirming the validity of our approach.

Analyzing the traces of the students' interactions with the system is a delicate task, often requiring further information about the context and not simply a one-to-one correspondence between behavioral indicators and learning preferences. In this chapter we reported and discussed the results of two experimental studies whose goal was to reveal relations between learning style and patterns of learner behavior. Next we introduced an automatic method for diagnosing student's ULSM preferences and validated it through experimental research. Finally we showed how we can use the detected preferences for categorizing the student in a traditional learning style model. In the next chapter we will show how we can adapt the course to best suit these learning preferences / styles that we identified so far.

Chapter 5

Adaptation Provisioning with respect to Learning Styles

In the previous chapter we proposed a method for the implicit identification of student learning preferences. However, as we have pointed out, modeling the learner is not a goal in itself. The value of a student model lies in its usability for providing a learning experience which is most beneficial for the student. Specifically, this could mean several things: in some cases, the most suitable attitude is to offer the student the educational resources that match their learning preferences, in terms of media type, order of resources, communication and collaboration facilities, level of navigation guidance etc. In other situations, students could benefit more from being faced with a mismatched learning environment, which provides the necessary challenge to boost learning (Kelly and Tangney, 2006). Moreover, when the learners are offered first the educational content that doesn't match their learning preferences, they will usually not limit themselves to that particular resource, being inclined to access more of the available resources on the subject. Finally, in some cases the learner model may be used not for triggering adaptation actions but solely for offering the student an insight into his/her learning preferences (Coffield et al., 2004a).

This chapter is concerned with how courses can be adapted to the learning preferences of the students. We start with a critical review of existing approaches, overviewing the adaptation methods used in LSAES, as well as summarizing the findings of the reported experimental results. Next, in section 5.2, we introduce our own approach, in the form of adaptation rules and their implementation as adaptation techniques. Finally, in section 5.3 we evaluate our method experimentally and report the results of our study (student satisfaction, performance, efficiency and effectiveness).

5.1. Critical Review of Existing Approaches

5.1.1. Methods and Techniques for Providing Adaptivity in LSAES

While in the previous chapter we discussed the state-of-the-art LSAES from the point of view of their modeling methods, in this section we address the adaptation approaches provided by these systems. Some of them combine adaptation provisioning based on several criteria: learning styles, knowledge level, goals etc – however in what

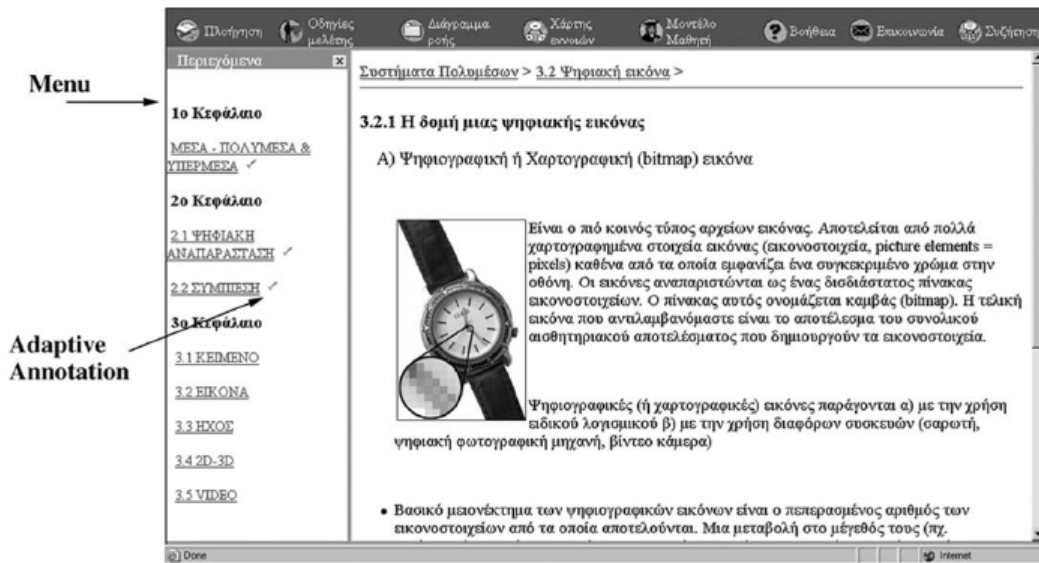
follows we are only interested in the adaptation techniques used for learning style personalization.

- CS383 (Carver et al., 1999) - The adaptation is done at the presentation level, by means of the sorting fragments technique (according to the suitability for each of the 3 constructs of the Felder-Silverman model: sensing/intuitive, visual/verbal, sequential/global)
- AES-CS (Triantafillou et al., 2003) – uses both adaptive presentation technique and adaptive navigation support to individualize the information and the learning path to the field dependence (FD)/field independence (FI) characteristic of the student (Witkin, 1962). Specifically, AES-CS uses conditional text and page variants to present the information in a different style: from specific to general in case of FI learners (who have an analytic preference) and from general to specific in case of FD learners (who have a global preference). AES-CS offers also two control options: program control for FD learners, by means of which the system guides the learner through the learning material; learner control for FI learners, by means of which the learners can choose their own learning paths, through a menu.

Since FD learners benefit more from instructions and feedback (Jonassen and Grabowski, 1993), an additional frame at the bottom of the page is used to provide them with explicit directions and guidance. This frame is missing in case of FI learners, who prefer few instructions and feedback. Similarly, in case of self-assessment tests, the feedback provided for FI learners is less extensive than in case of FD learners. Finally, FD learners are offered two navigational tools in order to help them structure the learning material and create the big picture: a concept map (a visual representation of the domain concepts and the relations between them) and a graphic path indicator (presenting the current, the previous and the next topic). Figure 5.1. illustrates the application of the above adaptation techniques for FI (5.1.a) versus FD learners (5.1.b).

Furthermore, AES-CS allows students to modify the adaptation options provided by the system, making their own choices between program / learner control, minimal / maximal feedback etc.

a)



b)

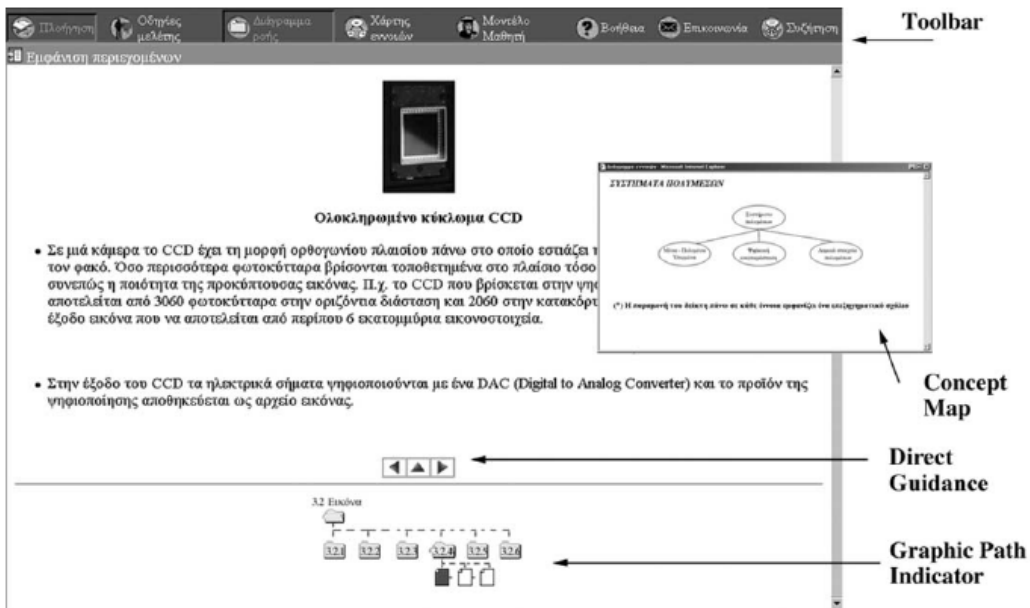



Figure 5.1. A snapshot from AES-CS system, with a course page adapted for:
 a) FI learners; b) FD learners (Triantafillou et al., 2003)

- INSPIRE (Papanikolaou et al., 2003; 2006) – uses adaptive presentation techniques to adapt the learning content to the 4 learning styles in Honey and Mumford model (2000): Activist, Pragmatist, Reflector and Theorist. All learners are presented


with the same knowledge modules, but their order and appearance (either embedded in the page or presented as links) differs for each learning style. Thus for Activists (who are motivated by experimentation and challenging tasks), the module "Activity" appears at the top of the page, followed by links to examples, theory and exercises. In case of Pragmatists (who are motivated by trying out theories and techniques), the module "Exercise" appears at the top of the page, followed by links to examples, theory and activities. Similarly, in case of Reflectors the order of modules is: examples, theory, exercises, and activities, while in case of Theorists the order is: theory, examples, exercises and activities. The system offers also the students the possibility to choose their preferred order of studying. Figure 5.2 offers a comparative view of the same course page as presented to Activists (5.2.a) versus Reflectors (5.2.b).

- Tangow (Carro et al., 2001) is based on a similar adaptation approach, but uses two of the FLSM dimensions: sensing/intuitive and sequential/global and only two types of modules: "example" and "exposition". For example, in case of sensing learners, the students are first presented with an example and only after that with exposition regarding that concept.

a)




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Activity

1. Επισκεφθείτε την ηλεκτρονική διεύθυνση http://www.wjv.cs.uni-sb.de/~kroening/cache_eng/ και επιλέξτε το σύνδεσμο Cache-o-Mat.
2. Πειραματιστείτε με το ρυθμό αποτυχίας της συνολο-σχετιστικής κρυφής μνήμης 1-δρόμου, 2-δρόμων και 4-δρόμων (Associativity) αφού επιλέξετε το δοκιμαστικό πρόγραμμα (Benchmark) SPECint92 (008.espresso).
3. Για ενοποιημένη κρυφή μνήμη (Cache type) συνολοσχετιστικότητας 2-δρόμων και για το δοκιμαστικό πρόγραμμα SPECint92 (008.espresso) παρατηρήστε πως μεταβάλλονται οι ρυθμοί αποτυχίας (Miss-Rate) για τα διαφορετικά μεγέθη της κρυφής μνήμης (Cache size) που παρουσιάζονται μετά την εκτέλεση της προσομοίωσης.
4. Τι παρατηρείτε για τους ρυθμούς αποτυχίας της κρυφής μνήμης εντολών και δεδομένων (Cache type - κρυφή μνήμη εντολών και δεδομένων) συνολοσχετιστικότητας 2-δρόμων που παρουσιάζονται μετά την εκτέλεση της προσομοίωσης.


Για δεδομένα στα οποία δεν ορίζουμε τιμές και εμφανίζονται στην προσομοίωση διατηρείστε τις προτεινόμενες σε αυτήν τιμές.



Link to an Example
[Ο μέσος χρόνος πρόσβασης στην...](#)



Link to Hints from Theory
[Περιοχή...](#)



Link to an Exercise
[Εξασκηθείτε με το ρυθμό αποτυχίας και το μέσο χρόνο πρόσβασης στην κύρια μνήμη...](#)

b)



Υπολογισμός Μέσου Χρόνου Πρόσβασης



Example

Ο μέσος χρόνος πρόσβασης στην κύρια μνήμη δίνεται από τον παρακάτω τύπο:

Μέσος χρόνος πρόσβασης στην κύρια μνήμη = χρόνος επιτυχίας + ρυθμός αποτυχίας x ποινή αποτυχίας

Αυτός αποτελεί το γενικό τύπο ο οποίος ανάλογα με την κρυφή μνήμη που έχουμε (ενοποιημένη ή δεδομένων και εντολών) διαφοροποιείται, αφού το ποσοστό των προσβάσεων στην κύρια μνήμη που αναφέρονται σε εντολές και σε δεδομένα είναι συνήθως διαφορετικό.

Αναλύοντας λοιπόν τον παραπάνω τύπο, σε επιμέρους μέσους χρόνους πρόσβασης στην κύρια μνήμη τόσο για τις εντολές όσο και για τα δεδομένα, καταλήγουμε στον παρακάτω τύπο:

Μέσος χρόνος πρόσβασης στην κύρια μνήμη = % εντολές x (χρόνος επιτυχίας + ρυθμός αποτυχίας εντολών x ποινή αποτυχίας) + % δεδομένα x (χρόνος επιτυχίας + ρυθμός αποτυχίας δεδομένων x ποινή αποτυχίας)

Ο ρυθμός αποτυχίας εντολών και ο ρυθμός αποτυχίας δεδομένων στην ενοποιημένη κρυφή μνήμη είναι ίδιοι.



[Link to Hints from Theory](#)



[Link to an Exercise](#)



[Link to an Activity](#)

Figure 5.2. A snapshot from INSPIRE system, with a course page adapted for:
a) Activist learners; b) Reflector learners (Papanikolaou et al., 2006)

- Heritage Alive Learning System (Cha et al., 2006b) – The learning system interface is adaptively customized: it contains 3 pairs of widget placeholders (text/image, audio/video, Q&A board/Bulletin Board) each pair consisting of a primary and a secondary information area. The space allocated on the screen for each widget varies according to the student's FLSM learning style: e.g. for a Visual learner the image data widget is located in the primary information area, which is larger than the text data widget; the two widgets are swapped in case of a Verbal learner. Similarly, the Q&A Board and Bulletin Board are swapped in case of the Active versus Reflective learners. Figure 5.3 illustrates the placeholders roles and positions.

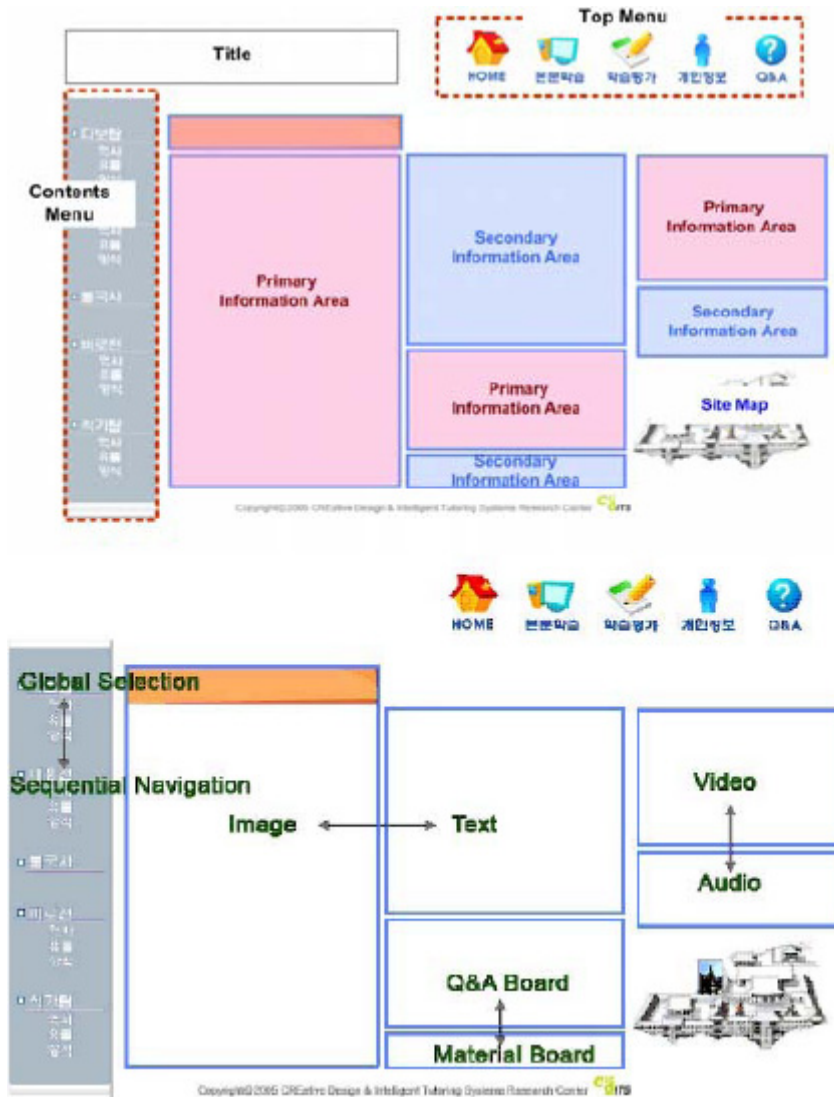


Figure 5.3. The interface template from Heritage Alive Learning System (Cha et al., 2006b)

- (Bajraktarevic et al., 2003) presents the course content in a specific layout, corresponding to the FSLSM sequential / global preference: pages for global students contain diagrams, table of contents, overview of information, summary, while pages for sequential learners only include small pieces of information, and Forward and Back buttons, as illustrated in Fig. 5.4.

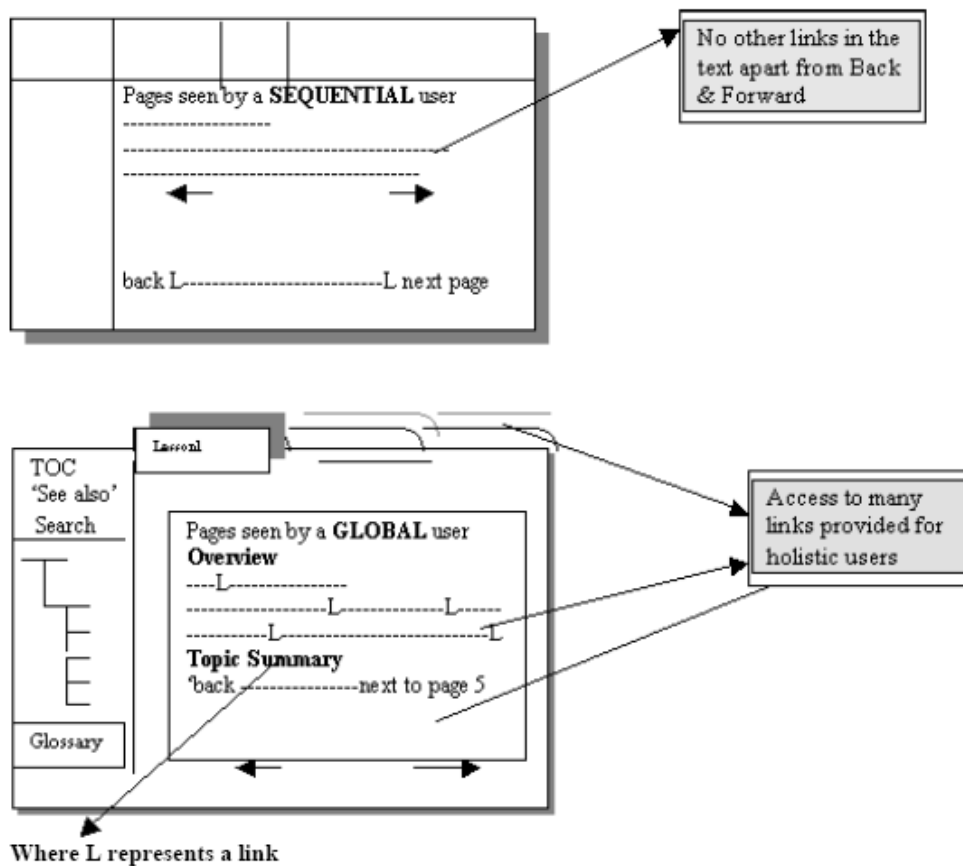


Figure 5.4. The interface template for sequential / global learners (Bajraktarevic et al., 2003)

- AHA! (version 3.0) (Stash, 2007) - uses an XML Learning Style Adaptation Language, called LAG-XSL, based on the LAG language, generalized adaptation model for generic adaptive hypermedia authoring (Cristea and Calvi, 2003). LAG-XSL is a high level language, including adaptation actions such as: *selection* of different representations of concepts (media, level of difficulty, type of activity) and *sorting* of concepts. By means of these actions, authors can define their own adaptation strategies for their own learning styles. There are two types of such strategies that can be defined: instructional strategies (for providing a certain selection of items, order of information or navigation paths) and *instructional meta-strategies* or *monitoring strategies* (for inferring preferences for certain items, items order and navigation paths). However, there is a limitation in the types of strategies that can be defined and consequently in the set of learning preferences that can be used. (Stash, 2007) includes examples of 3 instructional strategies (for verbalizer versus imager style; global versus analytic style; activist versus reflector style) and 2 meta-strategies (for inferring preference for text versus image and for navigation in breadth-first versus depth-first order). Figure 5.5 shows the student view of one of these instructional strategies (activist versus reflector style).

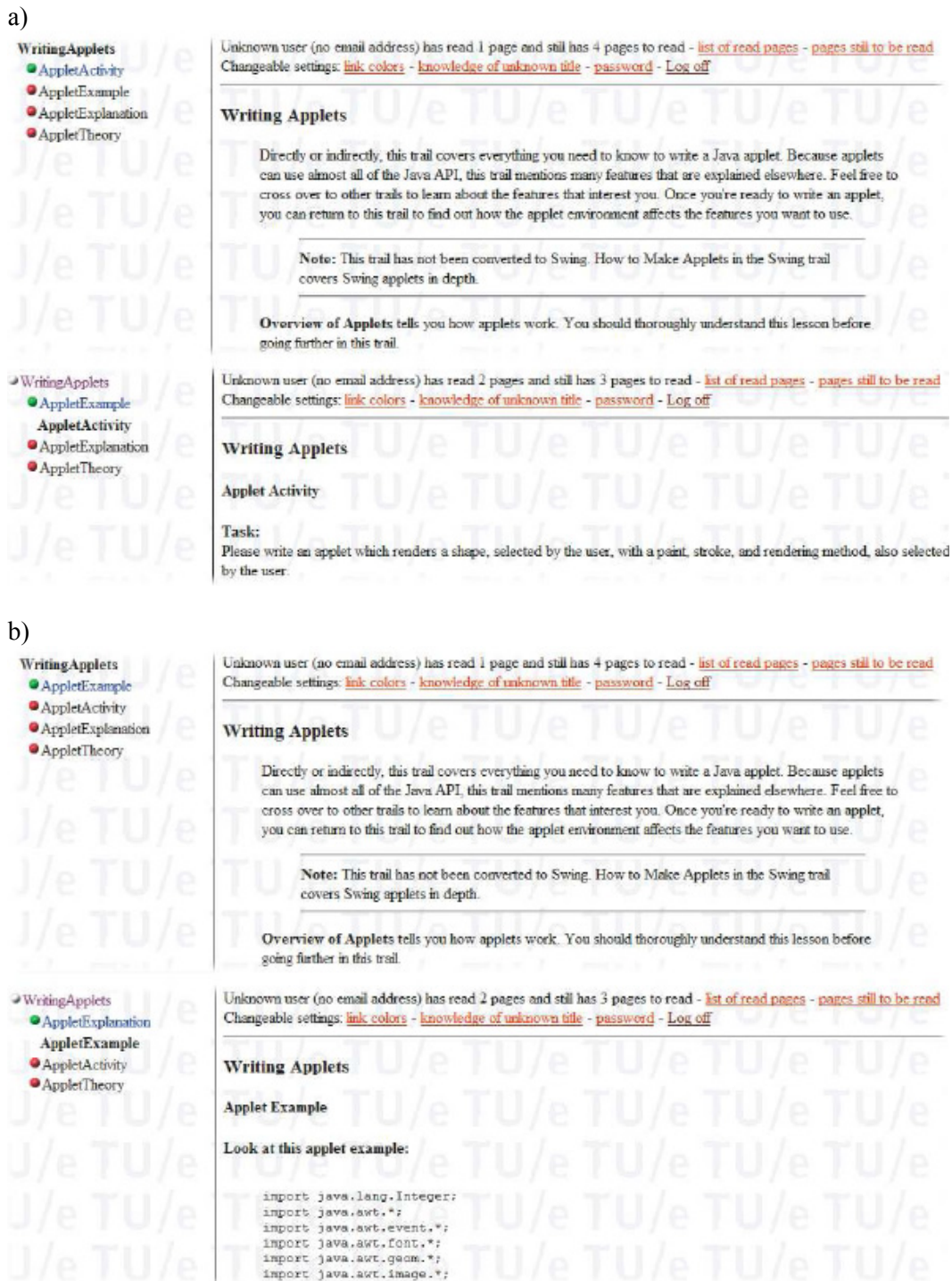


Figure 5.5. A snapshot from the AHA! system, with a page adapted for: a) activist learner; b) reflector learner.

- (Graf, 2007) – uses adaptation features such as: order of examples, exercises, self assessment tests and content objects and number of presented examples and exercises to adapt the course to the four FLSM dimensions.

5.1.2. Experimental Studies in LSAES

As already mentioned in Chapter 3, 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 3 studies in the latter category, which we will briefly present here.

- (Mitchell et al., 2004) – reports 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 versus field independent preference using the Cognitive Styles Analysis measuring instrument (Riding, 1991). Next they followed two 25-minutes 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 normal 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). Authors interpret 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) – presents a study involving 221 undergraduate and postgraduate students who were classified as visual, verbal or bimodal using the Felder-Soloman Inventory of Learning Styles. 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 WHURLE learning environment 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 authors acknowledge the existence of many uncontrolled variables that could have influenced the study and also that "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". The final conclusions 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 were found between matched and mismatched users in terms of sequential versus global learning style.

Next we present two of the studies that reported 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 versus global by using the ILS questionnaire. 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 students in pre and post-tests were recorded, as well as their browsing times. The statistical analysis showed that 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, 2007) performed a study involving 235 students who followed a course on object oriented modeling using a version of Moodle extended with adaptation capabilities. The students completed the ILS questionnaire, being classified on 3 of the 4 FLSM dimensions (active/reflective, sensing/intuitive, sequential/global). 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 final exam and the percentage of requests for additional LOs were recorded and analyzed. 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). 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), (Papanikolaou et al., 2003), (Pask, 1988), (Sangineto et al., 2007), (Triantafillou et al., 2003), (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.

An interesting and somehow surprising result was obtained by (Kelly and Tangney, 2006), who used 47 13-year old boys to analyze 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 students with medium and high activity levels was not significantly different in case of matched versus mismatched environments, as these students automatically involved themselves in alternative modes of thinking by exploring a number of different resources. However, in case of low activity students, the learning gain was significantly higher when students were presented with mismatched resources. 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, 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. The findings of this study suggest that the prior level of knowledge and student motivation should also play a role in adapting the environment to student's learning styles.

So far we have analyzed and discussed the adaptation methods and techniques used in related works, as well as their reported influence on the learning process. In what follows we will introduce our own approach to adaptation provisioning (in section 5.2) and study its effects (in section 5.3).

5.2. Adaptation Rules and Adaptation Techniques

As we have seen in chapter 4, although the ULSM model includes a set of low-level learning preferences (feature-based modeling), it also offers the possibility to infer the categorization of the students in the most popular learning style models available (stereotype-based modeling). Therefore adaptation can be done both starting from the ULSM preferences and from the traditional learning style models. This is why in this section we will illustrate both approaches, presenting the corresponding adaptation logic.

5.2.1. Adaptation Rules for Traditional Learning Style Models

We have proposed an initial formalization of knowledge about learning styles and its application in an adaptive educational hypermedia system, as modularized sets of rules. In our opinion the main achievements of our work are threefold: i) separation of knowledge about learning styles as modularized sets of rules; ii) explicit representation of the rules, encouraging their understandability, maintainability and reusability; iii) facilitation of appropriate implementation of the rules in an adaptive educational hypermedia system.

The development of these adaptation rules was a delicate task, since it involved interpretation of the literature in order to identify the prescriptive instructional guidelines. Indeed, apart from defining the characteristics of the learners belonging to each learning style, for most of the models there are proposed teaching practices that effectively address

the educational needs of students with the identified styles. However, as (Karagiannidis and Sampson, 2004) noted, "learning styles models are usually rather descriptive in nature, in the sense that they offer guidelines as to what methods to use to best attain a given goal; they are not usually prescriptive in the sense of spelling out in great detail exactly what must be done and allowing no variation: « prescription only applies to deterministic or positivistic theories, which are almost nonexistent in the social sciences » (Reigeluth, 1999)." 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 dealt with learning style based adaptation (as mentioned in the previous section), we extracted the adaptation rules for our LSAES.

We will first illustrate this approach with some simple rules for adapting an e-learning course to the needs of the students with different Felder-Silverman learning styles (Fig. 5.6), Herrmann learning styles (Fig. 5.7) and Kolb learning styles (Fig. 5.8) respectively.

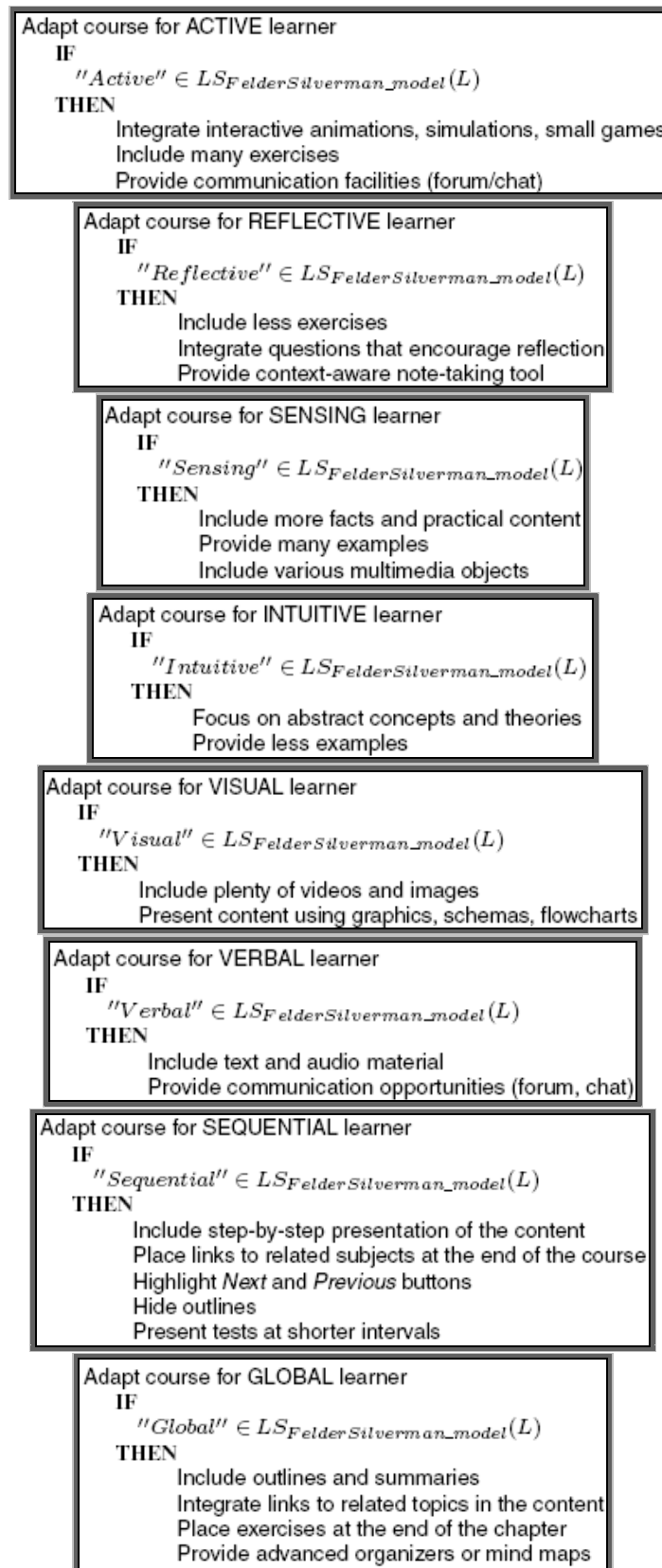


Figure 5.6. Adaptation rules for FSLSM dimensions

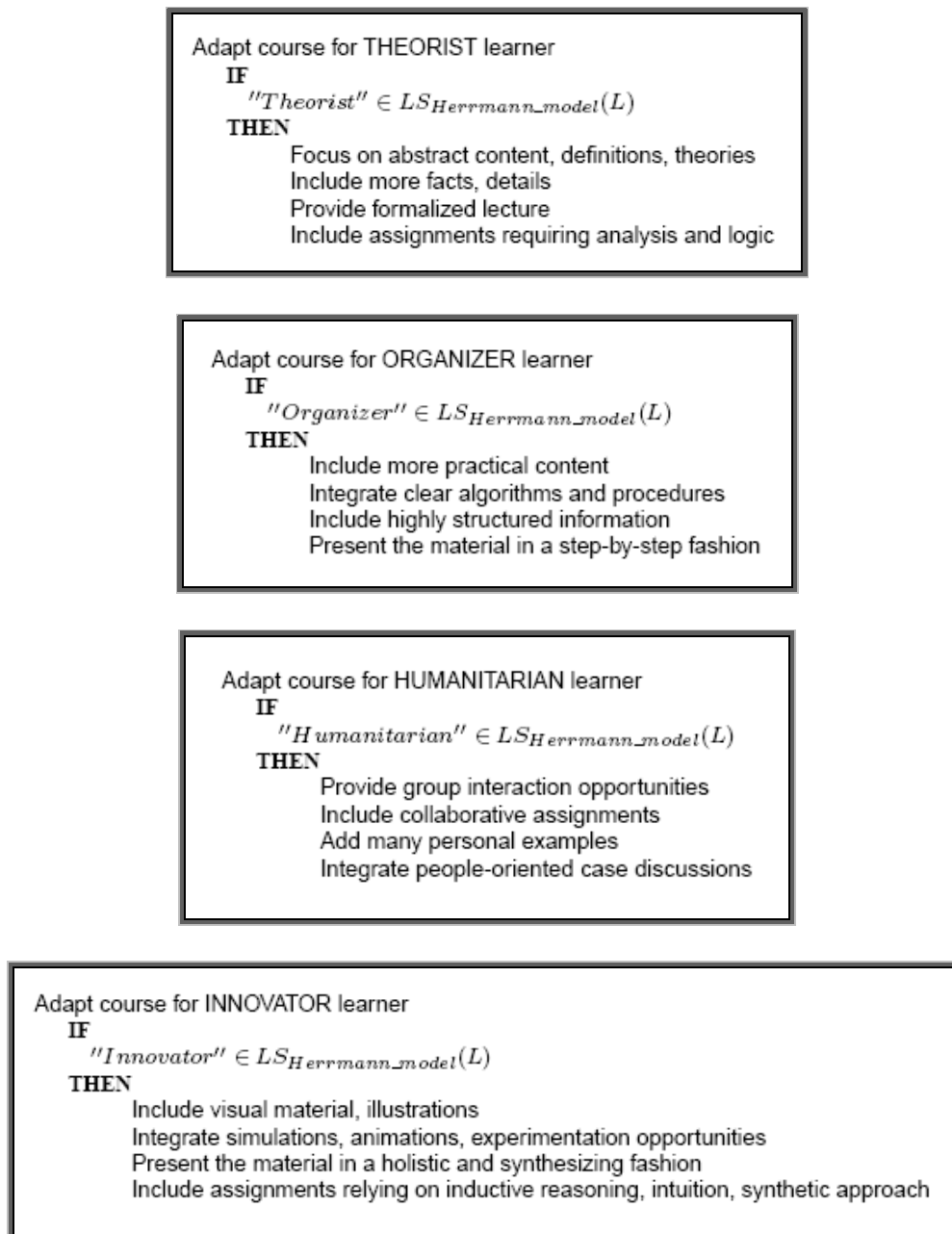


Figure 5.7. Adaptation rules for Herrmann learning styles

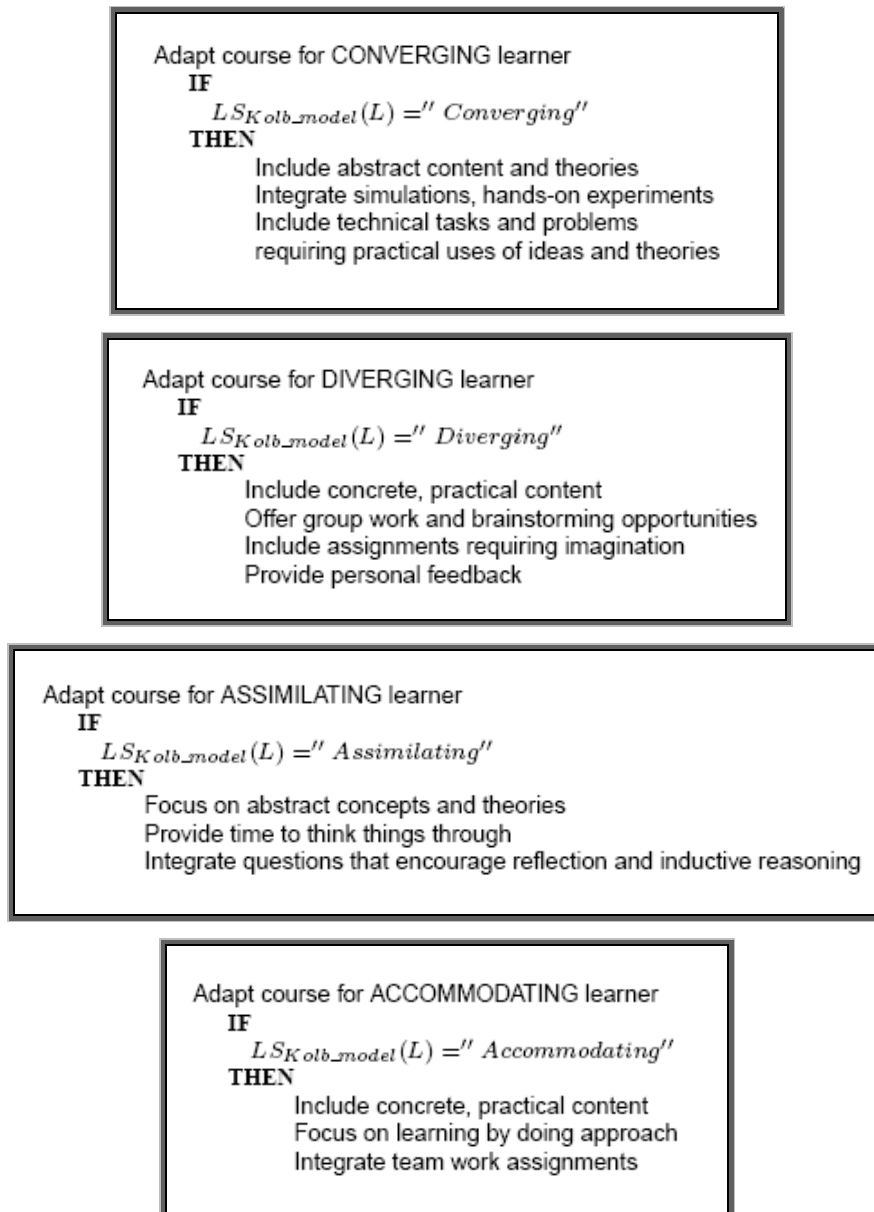


Figure 5.8. Adaptation rules for Kolb learning styles

5.2.2. Adaptation Rules for ULSM

Alternatively, starting from our feature-based modeling approach, we can associate adaptation rules for each of the identified learning preferences ($Pref(L) \subset Pref_ULSM$). Table 5.1 illustrates this approach with a subset of the ULSM preferences (i.e. ULSM', as defined in Chapter 4), providing the adaptation strategies that should be used for each preference, together with the corresponding adaptation techniques

(classified according to the levels of adaptation identified in (Brusilovsky, 2001; ALFANET, 2005)).

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.

Learning preference	Strategies for matched learning experience	Adaptation techniques
Visual	The course should include plenty of multimedia objects based on video and images; the content will be presented as much as possible using graphics and schemas.	Content level adaptation (specific media type filtering)
Verbal	The course should include more text and audio materials and provide communication opportunities (forum, chat).	
Abstract concepts and generalizations	The course should be focused more on theories, presentation of concepts and less on examples and concrete applications	Content level adaptation (content hiding, specific item filtering, sorting fragments, dimming fragments)
Concrete, practical examples	The course should be focused more on facts, practical aspects and examples. Each new concept will be first illustrated by an example and only then the theoretical aspects will be covered.	
Serial	The course should include a step-by-step presentation of the content, with a very regular structure and with the links to related or more advanced subjects placed at the end of the course, in order not to distract the learner. The navigation will typically be done sequentially, by means of the "Next" button which will therefore be highlighted and conveniently placed. The outlines will be hidden and the tests will be presented at shorter intervals.	Link level adaptation (link annotation, link generation) Content level adaptation (additional explanations, inserting fragments, sorting fragments)
Holistic	The course should include outlines and summaries for each course item, which will be presented at the beginning and end of each chapter and will be permanently accessible through a menu. The links to related or complex topics will be integrated in the content, to help situate the learnt subject and contribute to create the big picture. The exercises will be placed at the end of the	

	chapter, not after each course item, in order to give the users the opportunity to holistically understand the subject first	
Active experimentation	The course should include interactive simulations, in order to provide students with the needed "hands-on" experience. Interactive exercises will also be included, offering students the opportunity to try things out, using the "learning by doing" approach.	Content level adaptation (content hiding, specific item filtering, sorting fragments, dimming fragments)
Reflective observation	The course should include more lecture-like material, integrating questions that promote reflection and less interactive content. The exercises and simulations should be provided only after the student had the chance to think things through.	
Careful with details	The course should include many details (remarks, demonstrations, additional information etc), which help students understand the subject better.	Content level adaptation (content hiding, specific item filtering, dimming fragments, additional explanations, inserting fragments)
Not careful with details	The course should include less detail-oriented content and focus more on the fundamental aspects, in order to avoid student boredom.	
Individual work	The student should be offered the possibility to work on her own, providing her mainly with individual assignments.	Collaboration level adaptation (help to form the most appropriate workgroups taking into account student profile) Link level adaptation (link annotation, link generation)
Team work	The student should be offered the possibility to work in groups. The assignments should mainly consist of collaborative tasks. The course should include access to communication and collaboration tools (forum, chat, wiki, videoconference, whiteboard).	

Table 5.1. Ways of providing adaptivity for different learning preferences

It should be noted that our WELSA system was conceived to offer support for content level as well as for navigation level adaptation; collaboration level adaptation is outside the scope of our system and of this thesis.

As we can see, the adaptation logic can be decomposed into elementary actions, such as annotating, inserting, eliminating, sorting or moving learning objects. In the case of our LSAES, an adaptation rule can be abstracted as follows:

<p>General adaptation rule</p> <p>IF</p> <p>$X \in Pref(L)$</p> <p>THEN</p> <p><u>Action</u> <i>Object</i> {<i>Value</i>}</p>
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Object can be either a metadata element of a learning object, carrying a specific *Value* (as described in more detail in Chapter 6), or an interface element or a communication tool.

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 modeling and/or adaptation correspond to the actual needs of the students). Moreover, in case of a dynamic adaptation, this student's feedback could be used to adjust the student model and/or adaptation strategies.

Due to the above reasons, we decided to rely on sorting and adaptive annotation techniques rather than direct guidance or hiding/removing fragments. 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). Therefore in what follows we will present the actual adaptation rules that are implemented in WELSA, corresponding to each of the learning preferences in ULSM'.

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).

More formally¹:

<p>Adaptation rule for learners with "Visual" preference</p> <p>IF $p_{visual} \in Pref(L)$</p> <p>THEN <u>Sort</u> $dc : type \{Stillimage / MovingImage, Text / Sound\}$ <u>Dim</u> $dc : type \{Text, Sound\}$</p> <p>Adaptation rule for learners with "Verbal" preference</p> <p>IF $p_{verbal} \in Pref(L)$</p> <p>THEN <u>Sort</u> $dc : type \{Text / Sound, Stillimage / MovingImage\}$ <u>Dim</u> $dc : type \{Stillimage, MovingImage\}$ <u>Highlight</u> $Chat, Forum$</p>
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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. More formally,

<p>Adaptation rule for learners with "Abstract" preference</p> <p>IF $p_{abstract} \in Pref(L)$</p> <p>THEN <u>Sort</u> $LoType \{Fundamental, Illustration\}$ <u>Highlight</u> $LoType \{Fundamental\}$</p> <p>Adaptation rule for learners with "Concrete" preference</p> <p>IF $p_{concrete} \in Pref(L)$</p> <p>THEN <u>Sort</u> $LoType \{Illustration, Fundamental\}$ <u>Highlight</u> $LoType \{Illustration\}$</p>
--

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, unlike the less recommended "Previous" button and

¹ Note that $dc:type$ refers to the media type of the LO, while $LoType$ refers to the instructional role of the LO. Details regarding the LO metadata as well as the implementation of these rules in WELSA are presented in Chapter 6.

"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 holistic preference 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. More formally:

```

Adaptation rule for learners with "Serial" preference
IF
   $p_{serial} \in Pref(L)$ 
THEN
  Highlight Next_Button
  Dim Outline, Prev_Button
  Hide Outline, Prev_Button {bottomPage}
  Dim LoType {AdditionalInfo}

Adaptation rule for learners with "Holistic" preference
IF
   $p_{holistic} \in Pref(L)$ 
THEN
  Highlight Outline
  Dim Next_Button, Prev_Button
  Hide Next_Button, Prev_Button {bottomPage}
  Highlight LoType {AdditionalInfo}
  
```

In case of students with a preference towards active experimentation, the interactive LOs (such as exercises, simulations, real world problems etc) are particularly recommended, and therefore highlighted and placed before the rest of LOs. On the contrary, in case of students who prefer reflective observation, the interactive LOs are less recommended and placed after the LOs they accompany. More formally:

```

Adaptation rule for learners with "Active experimentation" preference
IF
   $p_{activeExperimentation} \in Pref(L)$ 
THEN
  Sort LoType {Interactivity, Fundamental / Illustration}
  Highlight LoType {Interactivity}

Adaptation rule for learners with "Reflective observation" preference
IF
   $p_{reflectiveObservation} \in Pref(L)$ 
THEN
  Sort LoType {Fundamental / Illustration, Interactivity}
  Dim LoType {Interactivity}
  
```

In case of students with a preference towards individual work, the system recommends individual assignments, while in case of students who prefer team work,

collaborative assignments are recommended and consequently highlighted. Additionally, the latter students are emphasized the possibility to communicate and collaborate with their peers by means of the dedicated tools (chat and forum). More formally:

```

Adaptation rule for learners with "Individual work" preference
IF
   $p\_individual \in Pref(L)$ 
THEN
  Highlight  $hasCompetency \{individual\}$ 
  Dim  $hasCompetency \{team\}$ 
  Dim  $Chat, Forum$ 

Adaptation rule for learners with "Team work" preference
IF
   $p\_team \in Pref(L)$ 
THEN
  Highlight  $hasCompetency \{team\}$ 
  Dim  $hasCompetency \{individual\}$ 
  Highlight  $Chat, Forum$ 
  
```

In case of a student who is careful with details, the system will emphasize the detail-oriented resources (additional information, remarks, demonstration), while in case of a student who is not careful with details, these resources will be less recommended. More formally:

```

Adaptation rule for learners "Careful with details"
IF
   $p\_carefulDetails \in Pref(L)$ 
THEN
  Highlight  $LoType \{AdditionalInfo, Remark, Evidence\}$ 

Adaptation rule for learners "Not careful with details"
IF
   $p\_notCarefulDetails \in Pref(L)$ 
THEN
  Dim  $LoType \{AdditionalInfo, Remark, Evidence\}$ 
  
```

Details regarding the LO metadata as well as the implementation of these rules in WELSA are presented in Chapter 6. In what follows we will show the way these adaptation strategies are visualized by the students, in the web browser. The course pages are taken from an Artificial Intelligence course, more specifically the chapter on Constraint Satisfaction Problems (CSP).

5.2.3. Visualization of Adaptation Rules

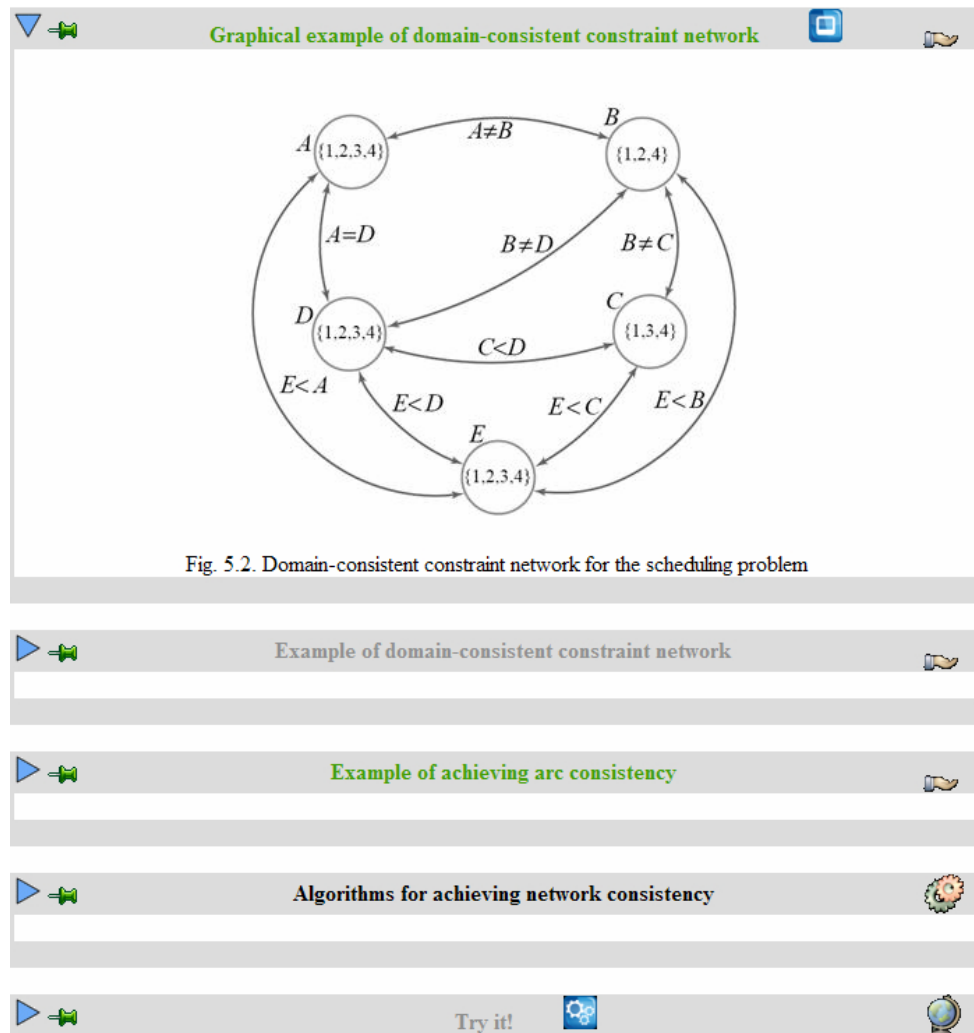


Figure 5.9. A snapshot from the WELSA system, with a course page adapted for a student with *Visual, Concrete, and Reflective observation* preference.

Figure 5.9 includes a fragment of a course page on Consistency Algorithms for solving CSPs, as presented to Student1, who has a *Visual* preference: consequently the image is marked as recommended and shown in an expanded state. Student1 also has a preference towards *Concrete, practical examples*, hence the consistency algorithms are first illustrated to her by 3 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 Student1, 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 Student1. Once the learner is familiarized with the examples, she 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 Student1 who has a *Reflective observation* preference. However, as mentioned before, these are mere recommendation: Student1 can choose to consult any LO that she wants and in any order.

The next figure (5.10) includes a fragment of the same course page, tailored towards the specific needs of a student with opposite preferences. Student2 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 which is suited to her *Active* side. Only afterwards is Student2 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 Student2 has a *Verbal* preference, the example which 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* Student2.

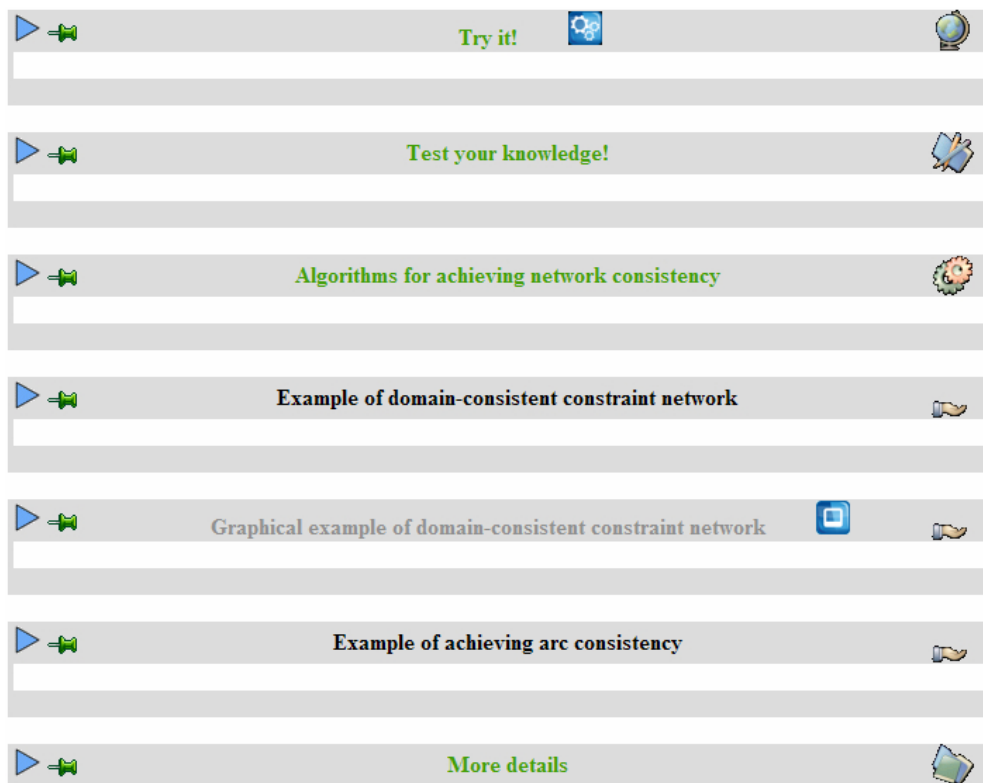


Figure 5.10. A snapshot from the WELSA system, with a course page adapted for a student with *Verbal*, *Abstract*, *Holistic* and *Active experimentation* preference

Figure 5.11 shows the course page on Generate-and-Test Algorithms for solving CSPs, as it appears to Student3. The Serial preference of the learner is reflected in the highlighted Next button. His Abstract preference is accommodated by presenting him first with the Generate-and-test procedure, while the examples are presented afterwards, once the theoretical part is covered.

The screenshot shows the Welsa system interface. At the top, there is a blue header with the 'Welsa' logo on the left and 'Account Logout', 'Welcome student3', and navigation links 'Home | Courses | Forum | Chat' on the right. Below the header, there are navigation buttons: 'Artificial Intelligence', 'PREVIOUS', 'OUTLINE', and 'NEXT' (which is highlighted in green). On the left side, there is a 'Chapters' sidebar with a list of 11 topics, with '5. Constraint Satisfaction Problems' selected. The main content area is titled 'Constraint Satisfaction Problems' and 'Solving a CSP'. It features a section for 'Generate-and-Test Algorithms' with a sub-section 'Generate-and-test procedure' (highlighted in green). This section contains text explaining that any FCPS can be solved by an exhaustive generate-and-test algorithm, defining the search space as the Cartesian product of variable domains $D = D_{v_1} \times D_{v_2} \times \dots \times D_{v_n}$. It also discusses the top-down proof procedure and the complexity of the search space, noting that it becomes intractable as the number of variables increases. Below this, there is a section for 'Generate-and-test example' (highlighted in green).

Figure 5.11. A snapshot from the WELSA system, with a course page adapted for a student with *Abstract* and *Serial* preference

Figure 5.12 shows the course page on "Posing a CSP", which starts with two recommended examples followed by a definition, since the student for which the page was generated has a *Concrete* preference. Since the learner has also a *Holistic* preference, he is advised to access the chapter Outline (which is presented in an expanded form in Fig. 5.12).

The screenshot shows the Welsa system interface. At the top, there is a blue header with the 'Welsa' logo on the left and 'Account Logout', 'Welcome student4', and 'Home | Courses | Forum | Chat' on the right. Below the header, there are navigation links: 'Artificial Intelligence', 'PREVIOUS', 'OUTLINE', and 'NEXT'. On the left side, there is a 'Chapters' sidebar with a list of 11 chapters. The main content area is titled 'Constraint Satisfaction Problems' and is divided into sections: 'Posing a CSP', 'Solving a CSP', 'Another example of a CSP', and 'Definitions'. A blue box highlights the 'Solving a CSP' section, which includes a sub-section 'Chapter 5. Constraint Satisfaction Problems' with a list of topics: 'Introduction', 'Posing a CSP', 'Generate-and-Test Algorithms', 'Backtracking Algorithms', and 'Consistency Algorithms'. The text in the main content area discusses solving problems as meetings of people or activities with constraints, and mentions variables X and Y with constraints like $X < Y$, $X \neq Y$, and $X = Y$.

Figure 5.12. A snapshot from the WELSA system, with a course page adapted for a student with *Concrete* and *Holistic* preference

5.3. Evaluation of the Adaptation Approach

5.3.1. Experiment Settings

In order to test our approach, we created a new chapter in the Artificial Intelligence course, dealing with "Constraint satisfaction problems" and we performed an experiment involving 64 undergraduate students. All the students had previously followed the non-adaptive course session on "Searching" and had also filled in the learning style questionnaires (ULSM, Felder-Silverman etc). Therefore the system already had all the information regarding the learning preferences of the students, both from their self-assessment and from their behavior in the system. Based on these data, we assigned students to two groups: one which will be provided with a matched version of the course (further referred to as "matched group") and one which will be provided with a mismatched version of the course (further referred to as "mismatched group"), with respect to the students' learning preferences. It should be noted that we took into consideration all the students, regardless of the level of intensity of their learning preferences, i.e. students with mild preference were offered the same adapted course as students with moderate or strong preference. Since we used the same subjects for the

adaptive and non-adaptive sessions we will be able to perform both an intrasubject and an intersubject comparability study.

First, all students had two hours to browse through the course; next the students were asked to take an assessment test and then to fill in two questionnaires, in which they could state their opinion on the course, the navigation paths they have taken, the effectiveness of the adaptation, the degree of satisfaction with the course etc.

In order to evaluate the adaptation process, we used two kinds of data: i) the behavior of the students in WELSA, as monitored and logged by the system; ii) the students' opinion about the adapted course, as stated in the questionnaires. Taking into account the fact that the amount of time students spent with the platform is limited (only one two-hour session), we would expect the effect of the adaptation to be rather small. Furthermore, as Coffield et al. pointed out in their study (2004a), the influence of learning styles on the learning gain of the students is quite small, compared with the influence of other factors such as prior achievement, ability or motivation. We will therefore expect an increase in the students' satisfaction, rather than an increase in the learning gain of the students.

In what follows we will present the results of the study, interpreting and discussing students' answers to the questionnaires as well as their behavior in the course.

5.3.2. Analyzing Behavioral Indicators

We investigated the following behavioral indicators:

- total learning time - t_{total}
- total number of hits on LOs - n_{LO}
- grade obtained on the evaluation tests - $grade_{tests}$
- time spent on recommended versus not recommended LOs –

$$t_{recommended_rel} = \frac{t_{rec_LO}}{t_{average_rec_LO}} / \frac{t_{notRec_LO}}{t_{average_rec_LO}} \text{ (as explained in Chapter 4,}$$

the average time is computed based on an average study time indicated by the course creator for each component LO)

- number of accesses of recommended versus not recommended LOs -

$$h_{recommended_rel} = \frac{h_{rec_LO}}{n_{rec_LO}} / \frac{h_{notRec_LO}}{n_{notRec_LO}}$$

- number of LOs accessed in the recommended order versus not recommended order -

$$n_{recommended_sequence_rel} = \frac{n_{rec_sequence}}{n_{notRec_sequence}}$$

- number of recommended versus not recommended navigation actions

$$n_{recommended_navigation_rel} = \frac{n_{rec_navigation}}{n_{notRec_navigation}}$$

First we computed the above values using our Analysis tool. Next we performed a statistical analysis on the data, 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). The tests were applied using SPSS software package (SPSS, 2008). The results are presented in table 5.2, including only those values for which we obtained statistical significance ($p < 0.05$). The mean values for each of the learning patterns, as well as t, u and p values are included.

Learning pattern	Matched group mean	Mismatched group mean	t-test / u-test
t_total	90	105	t = -2.03 p = 0.026
n_LO	45	58	u = 123.00 p = 0.039
t_recommended_rel	3.7	0.54	t = 3.05 p = 0.002
h_recommended_rel	2.12	0.73	t = 2.11 p = 0.023
n_recommended_navigation_rel	2.25	0.55	t = 2.31 p = 0.015

Table 5.2. Comparisons of pattern values for matched versus mismatched groups

The results obtained are very encouraging: the matched adaptation approach greatly increased the efficiency of the learning process, with a significantly lower amount of time needed for studying and a lower number of randomly accessed resources (lower level of disorientation). The effectiveness of the matched adaptation and its suitability for addressing students' real needs are also reflected in the significantly 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.

The only two patterns for which we did not obtain a significant difference are *grade_tests* and *n_recommended_sequence_rel*. The fact that we did not obtain a significant increase in the learning gain was expected and is consistent with other studies (Graf, 2007). However, it should be noted that this is also due to the following facts:

- only one 2-hour session took place; constantly applying a matching or mismatching approach could lead to more significant results

- students had the chance to access all LOs if they chose to do so, which means that a mismatched student could eventually access all the LOs that match her/his style, maybe with some loss of time and satisfaction.

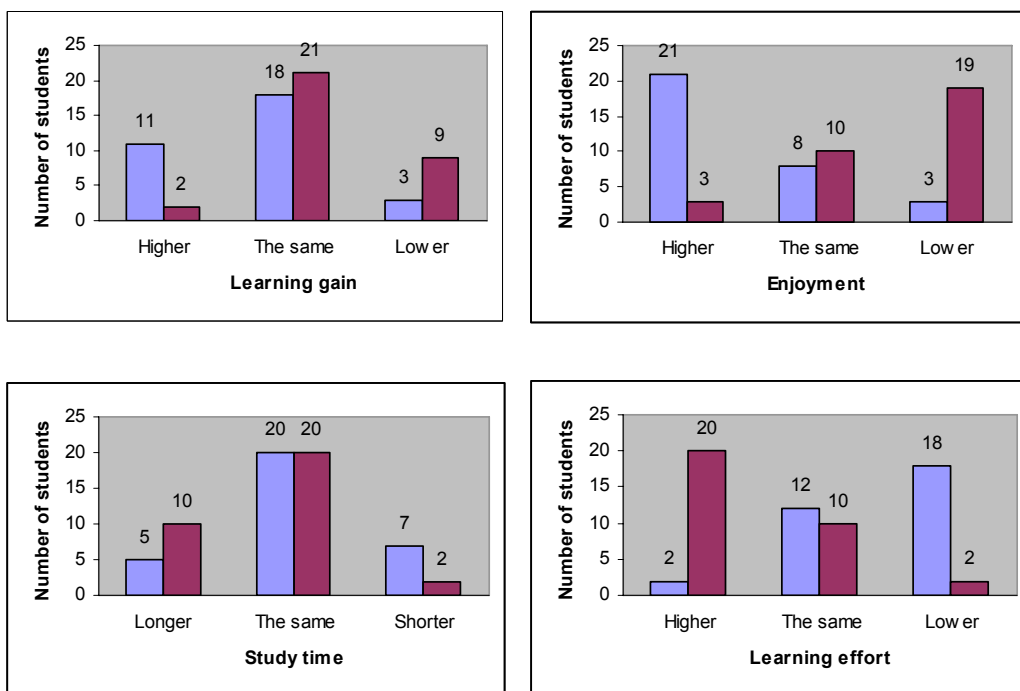
Regarding the number of LOs accessed in the recommended order versus not recommended order (*n_recommended_sequence_rel*), not obtaining a significant difference can be explained by the fact that a large majority of the students chose the order provided by the system, whether matched or mismatched. Further explanations for this behavior are offered in the next section.

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

5.3.3. Analyzing Students' Answers to Questionnaires

Perceived Difference between Adaptive and Non-adaptive Sessions

One of the first goals 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. Each of the 6 features was evaluated on a 3-point-scale and the results are presented in Fig. 5.13. Furthermore, for each question students had the possibility to justify / comment on their answers.



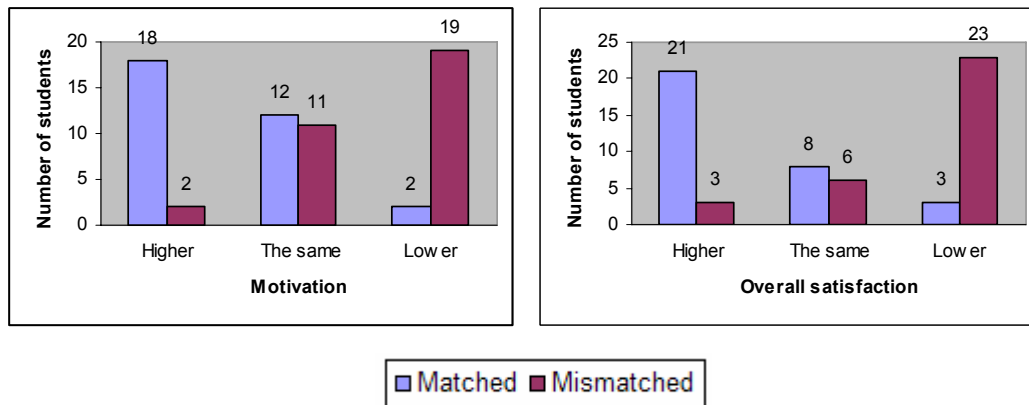


Figure 5.13. Comparison between the perceived learning gain, enjoyment, study time, learning effort, motivation and overall satisfaction in the adaptive versus non adaptive sessions

As we can see from Fig. 5.13, the greatest improvements between the adaptive and non-adaptive sessions were perceived by the students in the matched learning group in terms of enjoyment (65.63%), overall satisfaction (65.63%), motivation (56.25%) and learning effort (56.25%). At the same time, students in the mismatched learning group reported lower levels of overall satisfaction (71.87%), enjoyment (59.38%), motivation (59.38%), as well as an increase in the learning effort (62.5%). The differences in the learning gain and study time were less clear cut: 34.37% of the matched students described an increased learning gain and only 21.87% a reduced study time. Conversely, 28.12% of the mismatched students reported a decrease in the learning gain and 31.25% a longer study time.

The fact that more than half of the students reported a similar learning gain after the adaptive and non-adaptive sessions (56.25% of the matched learning group and 65.62% of the mismatched learning group) could be explained by the other factors that influence learning gain: all students were motivated to learn as well as possible in both sessions, since they were told that the grades of the evaluation tests would count for their final AI grade. Therefore they chose to spend more effort and more time to study, even if they found it less enjoyable. Moreover, it is important to note that the mismatching took the form of recommendations – all the resources were available to every student, who were free to choose the less recommended resources if they felt they were more suitable. However, when students are not under observation, are less compelled to study and are presented only with the mismatched learning content, the mismatching can prove more disturbing, making the students lose interest in the subject more quickly (as we will see further in our analysis).

There is a similar explanation regarding the fact that more than half of the students reported a similar study time in the adaptive versus non-adaptive sessions (62.5% from both the matched and mismatched learning groups). Since the students were

told that the experiment would last for 2 hours, most of them chose to use the whole time for studying, even if they could have finished in a shorter time. Students in the mismatched group used this time to check the non-recommended resources (that actually suited them better), while some of the matched students browsed through the non-recommended resources out of curiosity. As one of the students put it: "For the first pages, I checked the other resources to see why they were not recommended to me. But then I only used the recommended ones, since they were indeed more appropriate for me". Therefore we can assume that in case of an extended use of the system, once the students got to trust its decisions, they will also use it more efficiently. Furthermore, there were some diligent students who wanted to check all the resources to be sure they "didn't miss anything", thus ignoring the system's recommendations.

Degree of Following System's Recommendations and Perceived Usefulness of These Recommendations

The next goal of our questionnaire was to find out the proportion in which 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 page or in a different one and why. The results are presented in Fig.5.14.

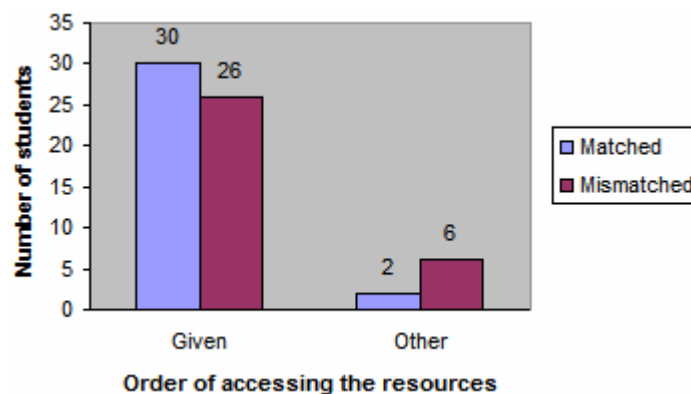


Figure 5.14. Order of accessing the resources in the adaptive session

In order to better understand and interpret these results we should compare them with the preferred order of access as declared by the students after the first (non-adaptive) session (see Fig. 5.15).



Figure 5.15. Order of accessing the resources in the non-adaptive session

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 pretty 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 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 students unthinkingly chose to follow the proposed order because "teachers know better", despite their own preferences, confirm 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. These statements come to confirm the importance of the ordering of resources, something that can be so easily achieved by means of adaptive hypermedia, but is so easily overlooked.

It should be mentioned that this question referred to the *initial* order of accessing the resources. Of course, some students mention that later they do come back to certain resources, for clarification or for more details (which is also reflected in the recorded behavioral patterns). However, it is the initial impression created by the learning material which is of a particular importance, especially for the less motivated and less perseverant students: it could make the difference between going on with the study or dropping out.

The same preference for being guided is reflected also in the answers to the next question: "In general, do you consider it useful to be recommended a learning path, particular resources, an order of accessing the resources or do you prefer to choose them by yourself?" 87.5% of the matched students stated that they prefer recommendations, while only 12.5% prefer to choose by themselves. Easy understanding and saving time were the highest cited advantages. 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", "Yes, a suggestion is always useful, even if you don't follow it after all", "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, only 56.25% reported a preference towards a recommended path versus a self-chosen one. This 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 adaptivity techniques that we employed were perceived as useful by the students: "Did you find useful the fact that the resources were marked as recommended / less recommended?" 81.25% of the matched students considered the annotation useful, as compared to only 15.62% of the mismatched students. As far as the percentage of students that actually followed the recommendation is concerned, 75% of the matched students reported following them. In some cases, this meant accessing only the recommended resources and completely ignoring the less recommended ones. In other cases, it only meant starting with the recommended resources: "Initially I have read only the recommended resources; then I came back to read all the resources where I thought it was necessary". The rest of the students reported accessing all the resources: "If they were introduced in the course, then it means they are useful", "I read everything – I always like to read more", "I didn't pay attention to the recommendations. I just accessed all the resources, from the beginning to the end". As for the mismatched students, 31.25% of them followed the recommendations. This relatively high percent can be explained by students' unconditioned trust in the system's/teacher's recommendations: "I thought they were meant to be accessed in this way". The rest of the mismatched students reported accessing all the resources, since "the recommended ones were the least preferred and least useful".

Degree of Adaptation Suitability

It should be noted that when they filled in the first questionnaire, the students were unaware of the existence of two groups (matched and mismatched), as at the beginning of the session they were all told that the course would try to match their learning preferences.

For the second questionnaire, however, the students were revealed their separation in two groups. One of the goals of this second questionnaire was to find out the

perceived degree of concordance / discordance between the course and the students' self-diagnosed learning preferences. "To which extent do you believe the course matched your real learning preferences?" was the question addressed to the matched students and "To which extent do you believe the course was contrary to your real learning preferences?" was the question addressed to the mismatched students. The subjects could choose from a 5-point-scale ("Very large", "Large", "Moderate", "Small", "Very small"). The results are presented in Fig.5.16.

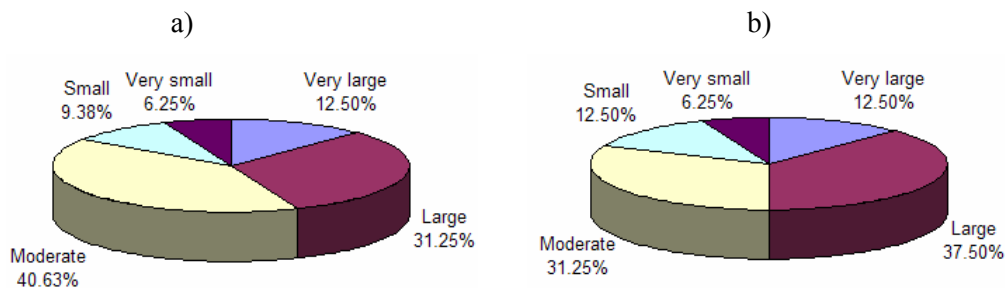


Figure 5.16. a) Perceived degree of concordance between the course and the matched students' self-diagnosed learning preferences
 b) Perceived degree of discordance between the course and the mismatched students' self-diagnosed learning preferences

The large percentage for "Moderate" responses in the matched students can be explained partially by the following fact: although they were told which was the set of learning preferences that the system tried to adapt to (i.e. *Pref_ULSM*), some students took into consideration all their learning preferences when answering this question, particularly those related to the physical learning environment. "I prefer to learn at home, in a more private space, not in the lab", "I prefer to learn in teams, with real interaction, not by chat", "I prefer to note down things when I learn", "The examples were helpful, but I would have understood better if the theory had been explained by a teacher". While being outside the scope of this thesis, these preferences should be remembered, as being of a particular importance for the learning process.

Extent of Adaptation Effect

The next survey item aimed at identifying the effect that this matching / mismatching had on the learning process. Students' answers to the question: "To which extent was this adaptation useful / disturbing / motivating for you?" are summarized in Fig.5.17.

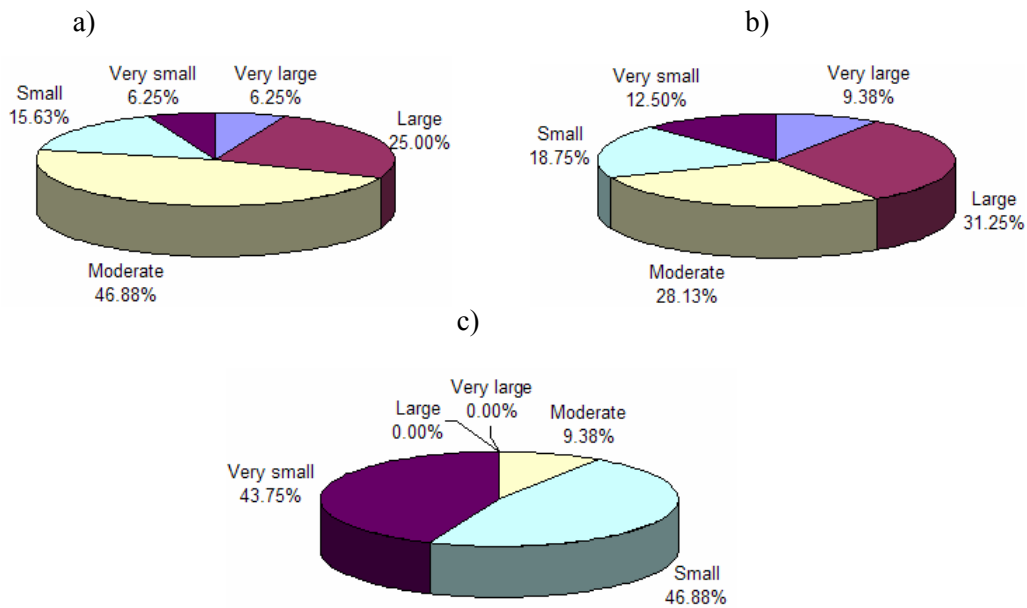


Figure 5.17. Perceived effect of the adaptation:
 a) usefulness degree in case of matched students
 b) disturbance degree in case of mismatched students
 c) motivation degree in case of mismatched students

As we can see, the majority of the matched students (78.13%) reported that the adaptation provided by the system proved useful for their learning process, at least to a moderate extent. Conversely, the majority of the mismatched students (68.76%) declared that the adaptation disturbed their learning process, at least in a moderate degree. The rest of the students, who were not affected by the mismatching, explained it by their attitude towards the course - ignore the recommendations and go back several times for some resources: "I didn't agree with the recommendations so I ignored them", "The disturbance was small, because even if examples were presented as less recommended to me, I ignored the recommendations and still read all of them", "Some parts were ordered contrary to my preferences, so I had to pass through them several times to understand", "I was quite confused at the beginning – I could have understood the course much faster in normal conditions".

As far as the level of motivation is concerned, almost all students reported a rather discouraging effect of the mismatching (90.63%). The explanations varied from quite radical: "You cannot possibly be motivated by something that you don't like", to more nuanced: "I'm usually not disturbed by a mismatched course (because I can adapt it to my preferences with a bit of effort), but I'm not motivated either", "I was just slightly demotivated because the material was quite easy. If the subject were more difficult and the material were contrary to my preferences, then I would probably be more inclined to give up".

5.3.4. Conclusions

The overall results of the experimental study proved the positive effect that our adaptation to learning styles has on the learning process.

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 fundamentals 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, 2002). 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.

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.

In this chapter we introduced some methods and techniques for adaptation provisioning and experimentally evaluated the effectiveness of our approach. We have thus addressed the second research question: "How can an AEHS perform adaptation according to different learning styles?". In the next chapter we will try to answer the third research question ("How can we build a learning style based adaptive educational system and how efficient is it?"), by providing technical details regarding the implementation of the underlying educational system: conceptual design, architecture, intelligent way of organizing the learning material, functionalities and technologies.

Chapter 6

WELSA System

In order to validate the modeling and adaptation techniques proposed in the previous chapters, we implemented them in an experimental educational system called WELSA (**Web-based Educational system with Learning Style Adaptation**).

WELSA's functionalities are primarily addressed at the students, who 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 analyzed 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 provides also functionalities for the teachers, who can create courses by means of the dedicated authoring tool; they can also set certain parameters of the modeling process: behavioral pattern weights and threshold values.

Secondarily and for the purpose of this thesis, WELSA is addressed also at researchers, who can use the learner data collected and processed by the system to evaluate the precision of the modeling method and the suitability of the chosen behavioral indicators and of the threshold values. They can also have access to aggregated information regarding the student actions and student preferences (e.g. total number of students with a particular learning preference, average reliability and confidence values).

Each of these functionalities will be presented in one of the sections of this chapter, as follows: first the overall system architecture is included in section 6.1, followed by the description of the intelligent way of organizing and indexing the learning material in section 6.2. Next, each of WELSA subcomponents is presented in turn, starting with the authoring tool (section 6.3), then the course player (section 6.4), the modeling component (section 6.5) and the adaptation component (section 6.6). The experimental validation of the system is done by creating and implementing a course module in the area of Artificial Intelligence (as described in section 6.7) and testing it with the students (as reported in section 6.8).

6.1. WELSA Architecture

The overall architecture of WELSA is illustrated in Figure 6.1.

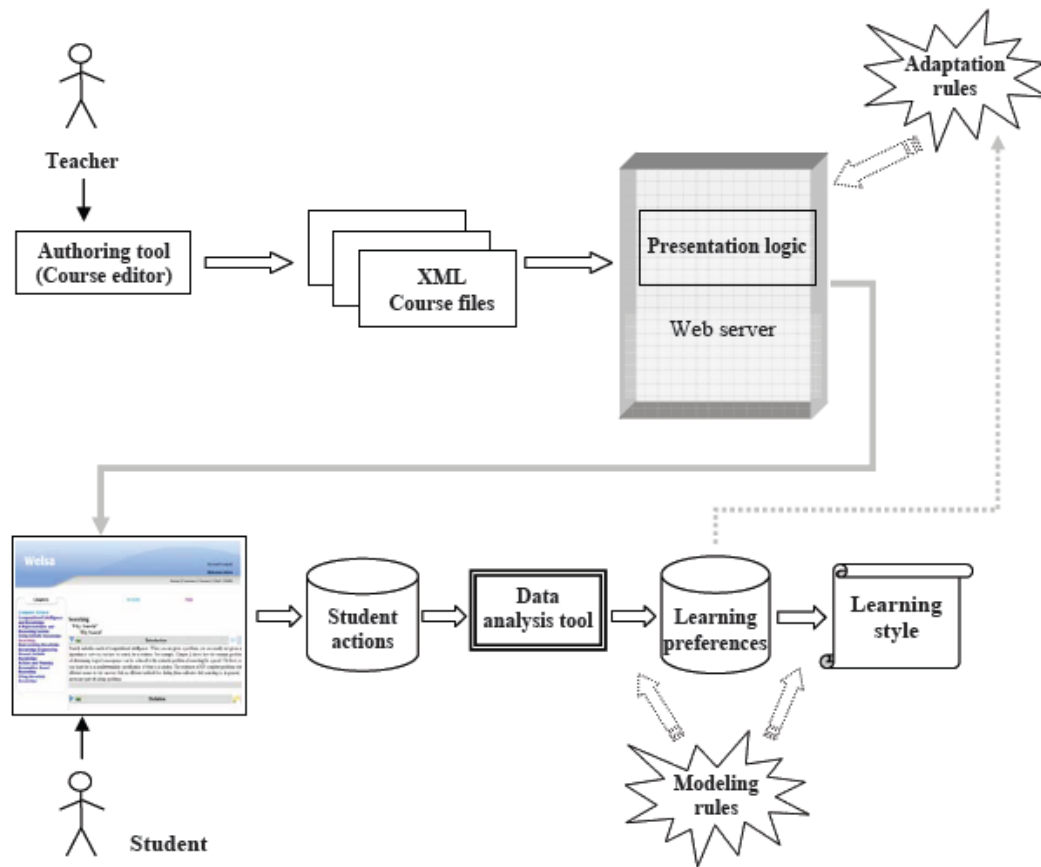


Figure 6.1. Overall WELSA architecture

As can be seen in Fig. 6.1, WELSA offers several functionalities:

- an authoring tool for the teachers, allowing them to create courses conforming to the internal WELSA format
- a course player (basic learning management system) for the students, enhanced with two special capabilities: i) learner tracking functionality (monitoring the student interaction with the system); ii) adaptation functionality (incorporating adaptation logic and offering individualized course pages)
- a data analysis tool, which is responsible for interpreting the behavior of the students and consequently building and updating the learner model, as well as providing various aggregated information about the learners.

We can thus identify two system views, corresponding to the two main actors involved in WELSA: student and teacher (author). Since it is an experimental system, there can be identified also a third role, the researcher, who mainly interacts with the Analysis tool, analyzing the modeling results and comparing them with those obtained by means of the questionnaires, as described in Chapter 4. Further details on the researcher role and the facilities offered to them by the system can be found in section 6.5.

As far as the implementation is concerned, Java-based and XML technologies are employed for all WELSA components. Apache Tomcat 6.0 (Tomcat, 2008) is used as HTTP web server and servlet container and MySQL 5.0 (MySQL, 2008) is used as DBMS. Further details will be presented in sections 6.2 – 6.6.

The first objective of WELSA system is to dynamically model the learner: identify the learning preferences by analyzing the behavioral indicators and then, based on them, infer the belonging to a particular learning style dimension. The second objective is to consequently adapt the navigation and the educational resources to match the student learning preferences. In order to achieve these two objectives, we need an intelligent way of organizing the learning material as well as a set of instructional metadata to support both the learner modeling and the adaptation, which are introduced in the next section.

6.2. Description and Organization of Instructional Resources in WELSA

In this section we need to answer one question: how do we categorize learning material so that we can identify the student preferences and also be able to select different content for different students? According to (Cristea, 2003), the existence of a static description of the learning content (metadata) is a necessary condition for introducing an adaptation model (dynamic description). We therefore address the problem of educational metadata in the following subsection, detailing the course organization in subsequent subsections. Our proposal for organizing and annotating the educational material was first introduced in (Popescu et al., 2008a; 2008f).

6.2.1. Educational Metadata

Educational metadata is a special kind of metadata that provides information about learning objects (i.e. any reproducible and addressable digital resource that can be reused to support learning (IMS MD, 2008)). Currently there are several initiatives for standardizing educational metadata, addressing the issues of reusability, interoperability, discoverability, sharing and personalization (Anido et al., 2002).

IEEE LOM (Learning Object Metadata) (IEEE LOM, 2008) is the most prominent standard, being elaborated by the IEEE Learning Technology Standards Committee. IMS Global Learning Consortium (IMS Global Learning Consortium, 2008) also contributed to the drafting of the IEEE LOM and consequently the current version of IMS Learning Resource Metadata specification (IMS LRM v. 1.3) is based on the IEEE LOM data model. LOM contains nine categories of metadata: General, Lifecycle, Meta-metadata, Technical, Educational, Rights, Relation, Annotation and Classification (see

Fig. 6.2). The attributes that are relevant from the point of view of instruction and pedagogy are the educational ones, specifically *Learning Resource Type*. Its possible values are: *Exercise, Simulation, Questionnaire, Diagram, Figure, Graph, Index, Slide, Table, Narrative Text, Exam, Experiment, Problem Statement, Self Assessment, Lecture*.

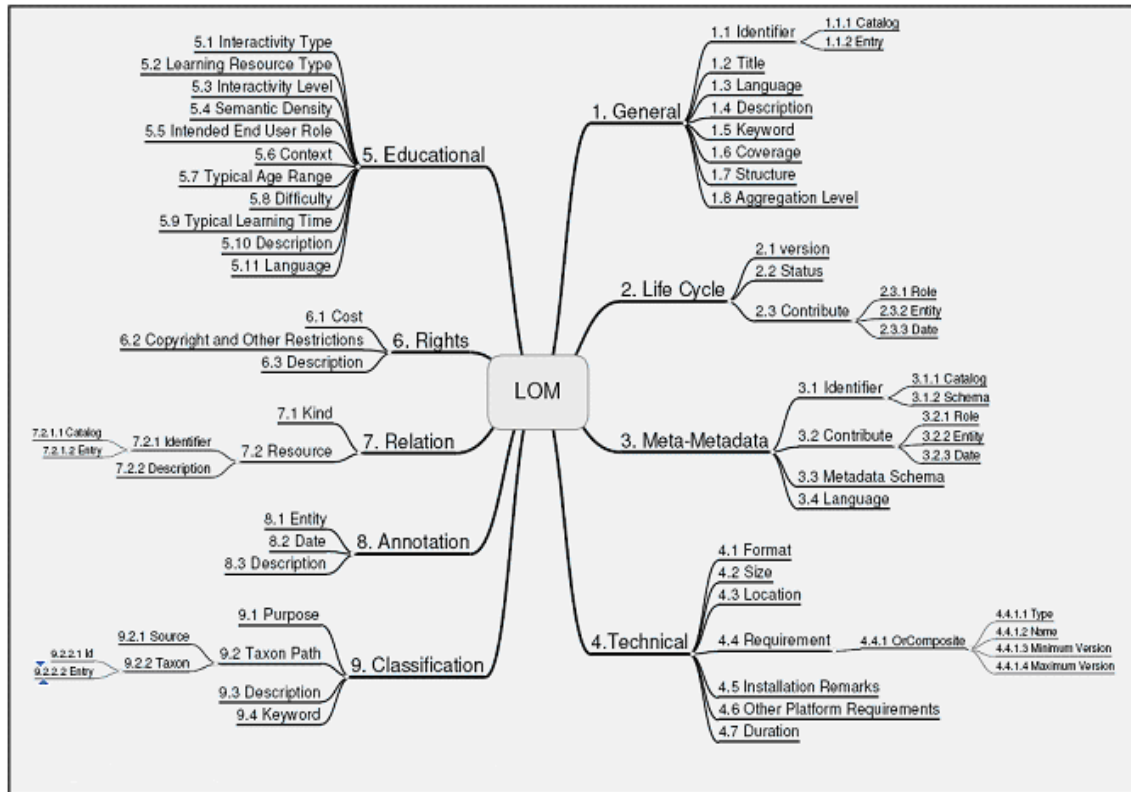


Figure 6.2. A schematic representation of the hierarchy of elements in the LOM data model (Barker, 2005)

Another widely known standard is *SCORM (Sharable Content Object Reference Model)* (ADL SCORM, 2008) which originates from e-learning requirements of the US Armed Forces, being produced by ADLNet (Advanced Distributed Learning Network) initiative. SCORM includes three types of learning content metadata: raw media metadata (that provide information about assets independently of learning content), content metadata (that provide information about learning content, independently of a particular content aggregation) and course metadata (that provide information about the content aggregation).

Dublin Core metadata standard (DCMI, 2008) is a simple yet effective general-purpose metadata scheme, for describing a wide range of networked resources. It was developed within the Dublin Core Metadata Initiative (DCMI). At present, there is a joint DCMI/IEEE LTSC Task Force activity, with the objective of developing a representation of the metadata elements of the IEEE LOM in the Dublin Core Abstract Model.

The main problem with these specifications is that they fail to include the instructional perspective (Ullrich, 2005). In case of LOM, the property *Learning Resource Type* attempts to address this issue, but mixes instructional and technical information. Thus some of the values describe the instructional role of the resource (*Exercise, Simulation, Experiment*), while others are concerned with their format (*Diagram, Figure, Graph, Slide, Table*). Moreover, some important instructional types are missing, such as *Definition, Example* or *Theorem*. In order to overcome this issue, Ullrich (2005) introduced an instructional ontology, which is domain independent and pedagogically sound. This is an ontology of instructional items, which is composed of two main classes: Concept (corresponding to Fundamental items, which describe central pieces of knowledge) and Satellite (corresponding to Auxiliary items, which provide additional information about the concepts); each of these two classes subsumes several other classes, as can be seen in Fig. 6.3. One of the most important advantages of this ontology is its pedagogical flexibility, being independent of a particular instructional theory. Moreover, as we will show further on, the ontology can also be enhanced to serve adaptivity purposes, from the point of view of various learning styles. Thus we will first describe the organization of the learning resources and afterwards we will introduce the educational metadata used.

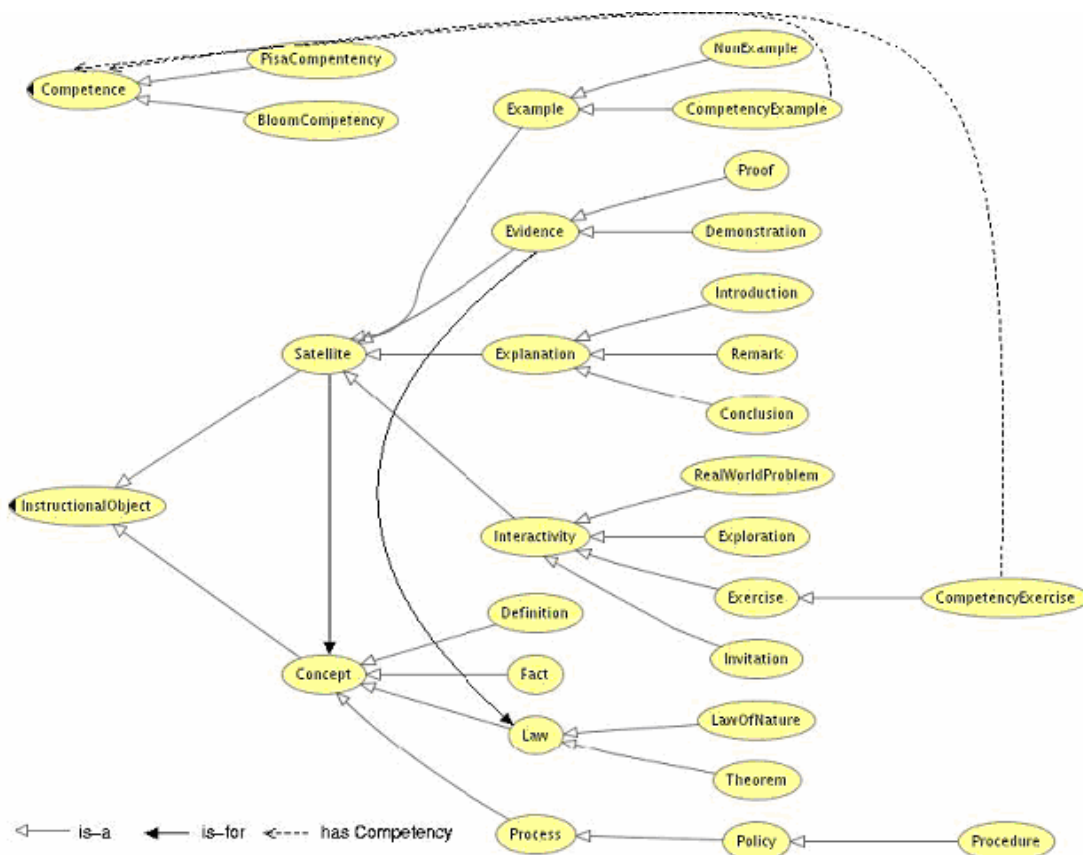


Figure 6.3. Ullrich's instructional ontology (Ullrich, 2005)

6.2.2. Organizing the Educational Material in WELSA

According to (IMS MD, 2008), learning objects represent any digital resources that can be reused to support learning. In our case, the most complex learning object (with the coarsest granularity) is the course, while the finest granularity learning object is the elementary educational resource. We have conceptualized the learning material using the hierarchical organization illustrated in Fig.6.4: each course consists of several chapters, and each chapter can contain several sections and subsections. The lowest level subsection contains the actual educational resources. Each such elementary learning object corresponds to a physical file and has a metadata file associated to it. This fine grained representation of the learning content is needed to insure the adaptation and modeling requirements.

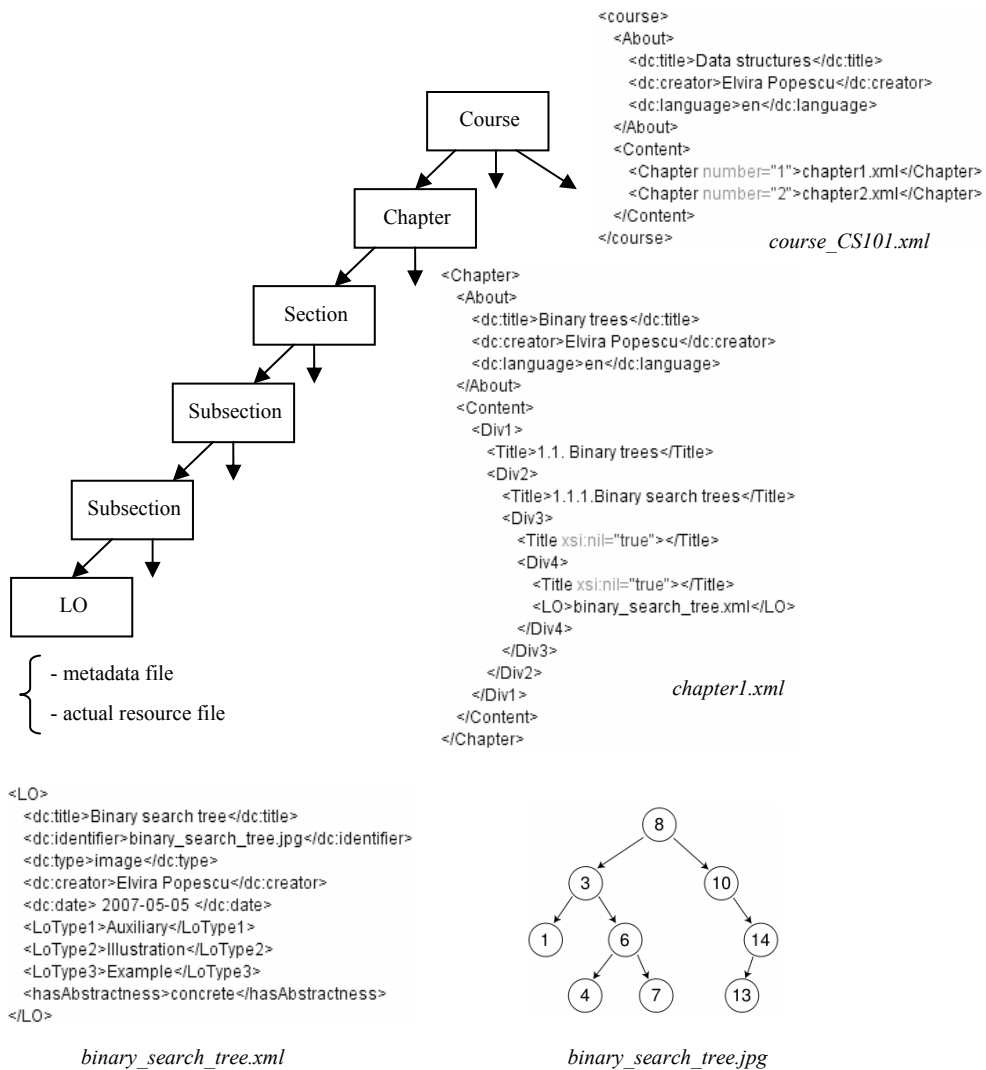


Figure 6.4. Organization of learning content in WELSA

Based on our teaching experience, this is the natural and most common way a teacher is usually organizing her/his teaching materials. Additionally, this hierarchical approach presents several advantages, facilitating:

- good reuse of the educational resources
- detailed learner tracking (since we know all the information about the learning resource that is accessed by the learner at a particular moment)
- fine granularity of adaptation actions.

In Fig. 6.5 and 6.6 we give a schematic representation of the XML schemas for the course and chapter files respectively, generated with Oxygen tool (Oxygen, 2008). The corresponding XSD files are included in Appendix A.

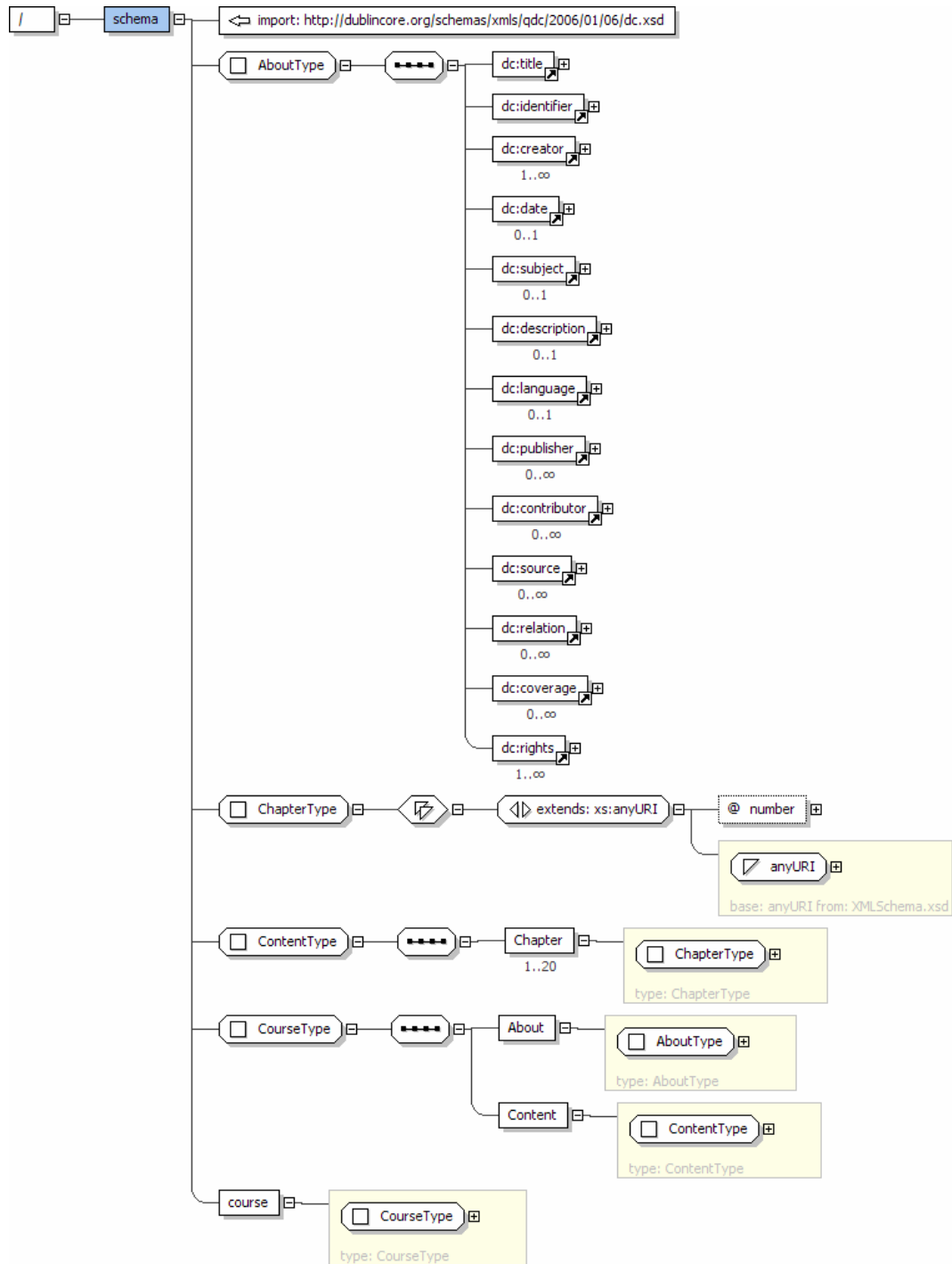


Figure 6.5. Graphical view of XML course file structure

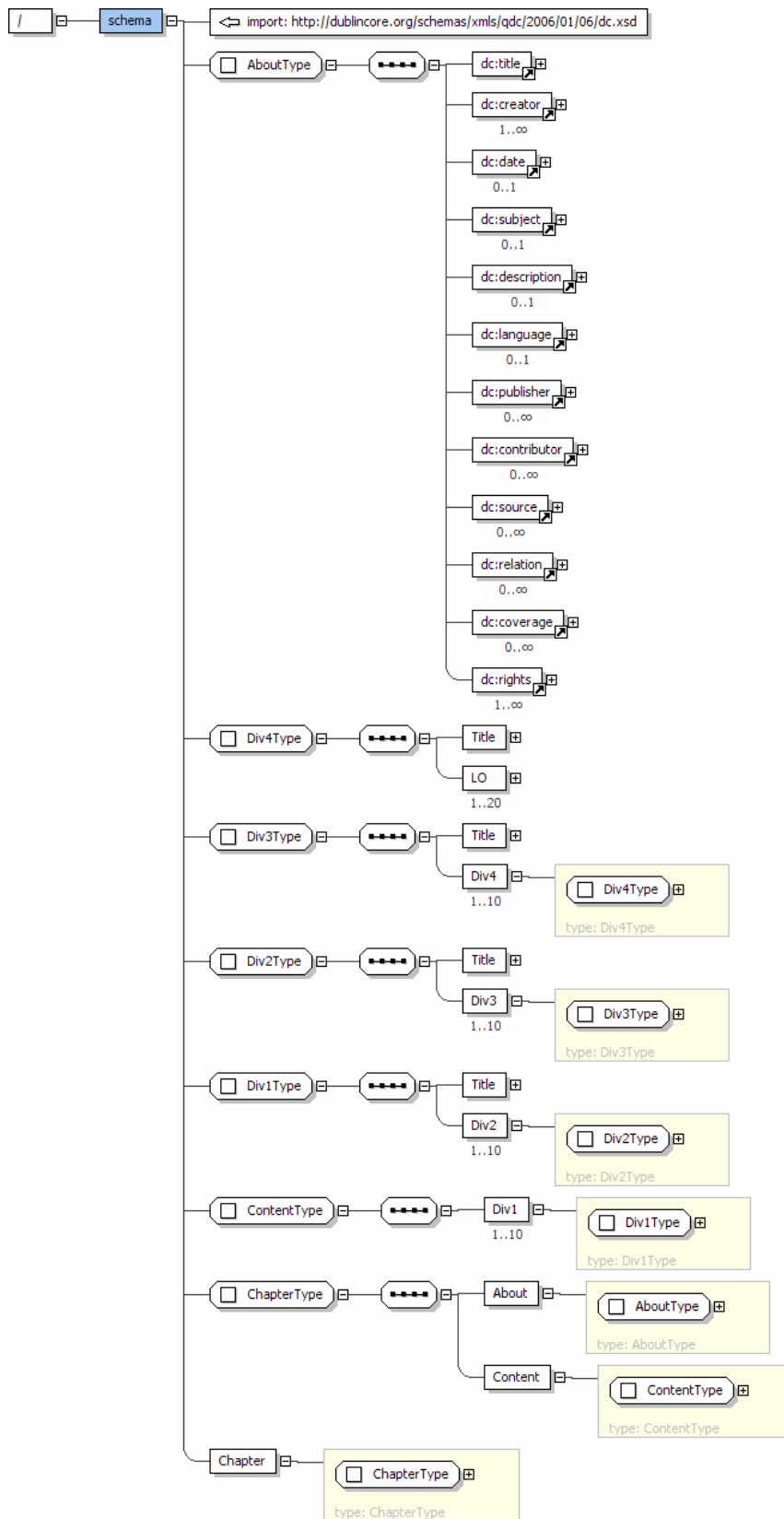


Figure 6.6. Graphical view of XML chapter file structure

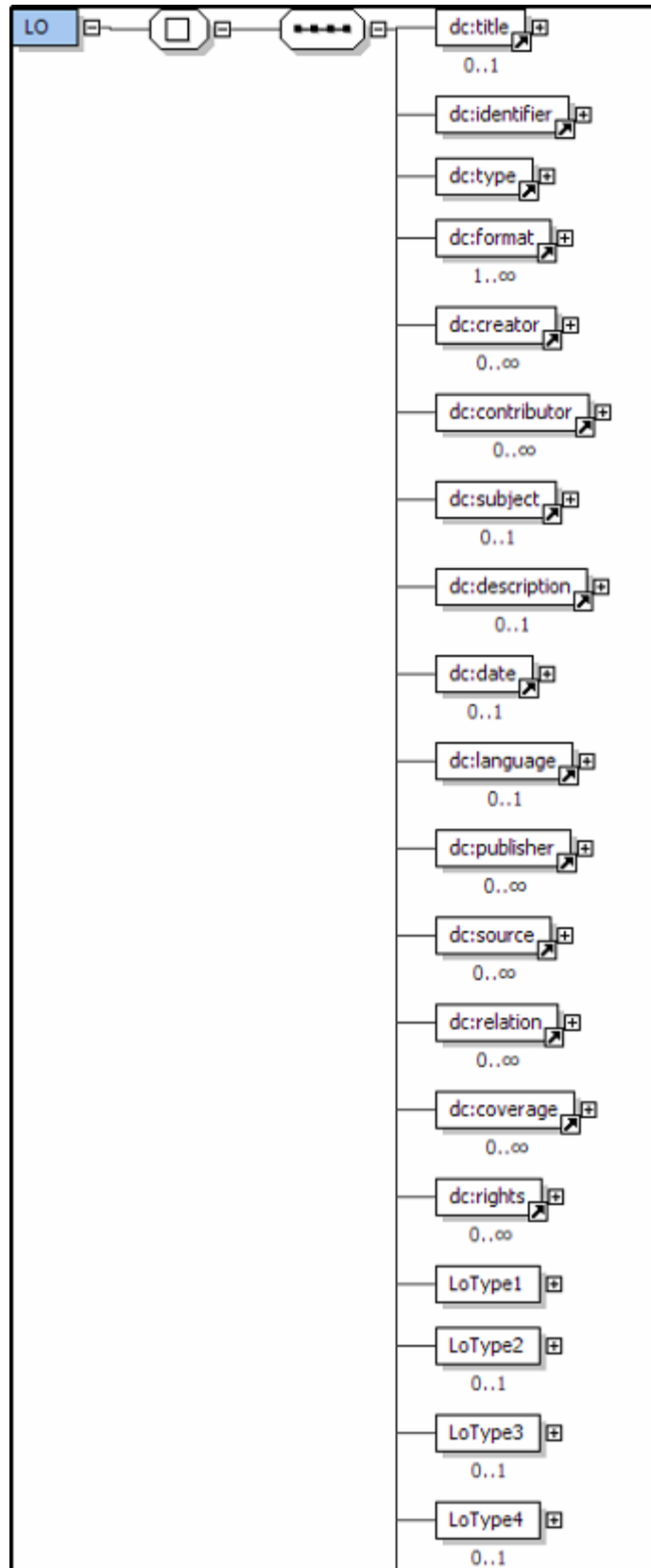
6.2.3. Indexing Learning Content in WELSA

As far as the educational metadata is concerned, one possible approach (which is used in (Gascuena et al., 2006)) would be to associate to each learning object the learning style that it is most suitable for. One of the disadvantages is that this approach is tied to a particular learning style. Moreover, the teacher must create different learning objects for each learning style dimension and label them as such. This implies an increase in the workload of the teacher, and also the necessity that she/he possesses knowledge in the learning style theory. Furthermore, this approach does not support dynamic learner modeling, since accessing a learning object does not offer sufficient information regarding the student (a learning object can be associated with several learning styles).

Instead, we propose a set of metadata that describe the learning object from the point of view of instructional role, media type, level of abstractness and formality, type of competence etc. These metadata were created by enhancing core parts of Dublin Core (DCMI, 2008) and Ullrich's instructional ontology (Ullrich, 2005) with some specific extensions to cover the requirements of a LSAES. Thus some of the descriptors of a learning object are:

- title (the name given to the resource) → *dc:title*
- identifier (a reference to the actual resource, such as its URL) → *dc:identifier*
- type (the nature of the content of the resource, such as text, image, animation, sound, video) → *dc:type*
- format (the physical or digital manifestation of the resource, such as the media type or dimensions of the resource) → *dc:format*
- instructional role, either i) fundamental: definition, fact, law (law of nature, theorem) and process (policy, procedure) or ii) auxiliary: evidence (demonstration, proof), explanation (introduction, conclusion, remark, synthesis, objectives, additional information), illustration (example, counter example, case study) and interactivity (exercise, exploration, invitation, real-world problem) → *LoType1, LoType2, LoType3, LoType4*.
- related learning objects: i) *isFor / inverseIsFor* (relating an auxiliary learning object to the fundamental learning object it completes); ii) *requires / isRequiredBy* (relating a learning object to its prerequisites); iii) *isA / inverseIsA* (relating a learning object to its parent concept); iv) *isAnalogous* (relating two learning objects with similar content, but differing in media type or level of formality).

A graphical representation of the metadata schema is included in Fig. 6.7. The corresponding XSD file is included in Appendix A.



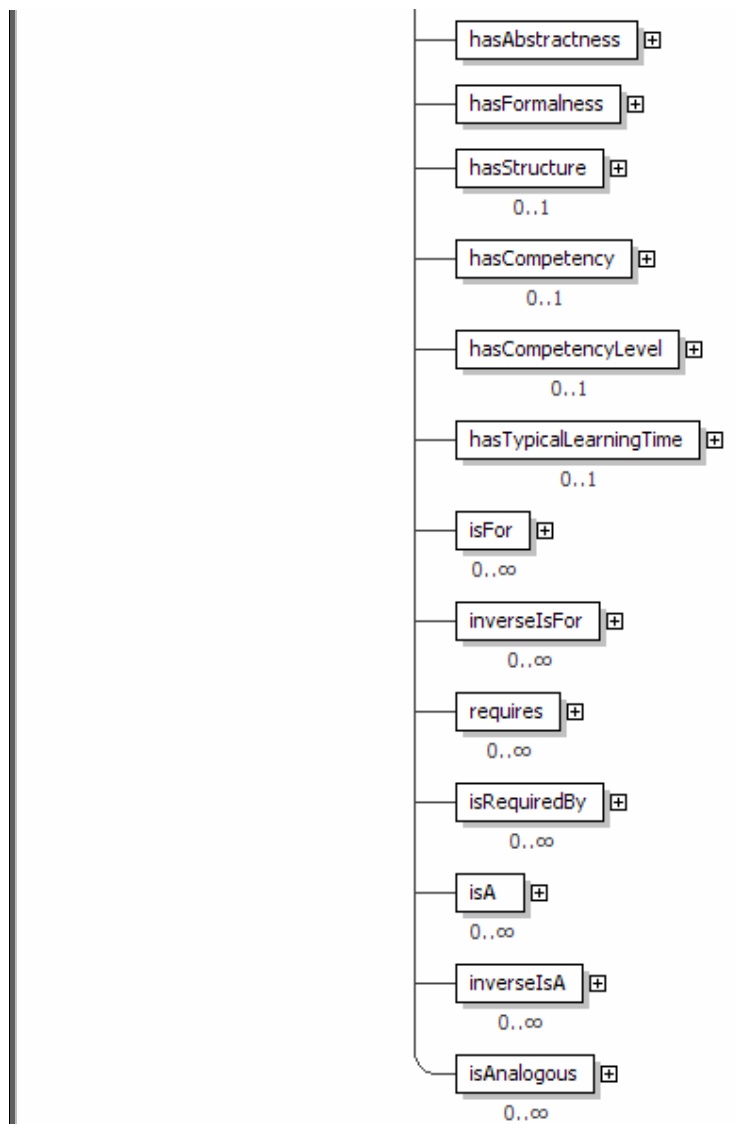


Figure 6.7. Graphical view of metadata schema

Obviously, these descriptors are independent of any learning style. However, by analyzing the interaction between the student and the learning objects described by these metadata (time spent on each learning object, order of access, frequency of accesses), the system can infer a particular learning preference of the student. Furthermore, the teacher has to supply only annotated learning content (the static description) while the adaptation logic (the dynamic description) is provided by the system. This means that the adaptation rules are independent of the learning content and that they can be supplied by specialists in educational psychology. Sections 6.5 and 6.6 will illustrate the use of these metadata for modeling the learner and providing adaptation respectively.

While the elements pointing to the instructional role of the learning objects (*LoType1*, *LoType2*, *LoType3*, *LoType4*) correspond to the pedagogical model, the

domain model is represented by means of the *dc:subject* element. Furthermore, the different relationships between the concepts are represented by means of the *isFor* / *inverseIsFor*, *requires* / *isRequiredBy*, *isA* / *inverseIsA* and *isAnalogous* metadata elements.

6.2.4. Related Approaches

Currently there are several works that address aspects related to ontologies and metadata for personalized e-learning, such as: (Al-Khalifa and Davis, 2006; Brown et al., 2005; Devedzic, 2006; Dolog et al., 2004; Dolog and Nejd, 2007; Gascuena et al., 2006; Geser, 2007; Shi et al., 2004). A few of them, that we will briefly discuss here, also take into consideration learning styles.

In case of (Gascuena et al., 2006) the ontology is tied to a particular learning style model, namely Felder-Silverman (FSLSM). There is a special class, *LearningStyle*, which represents the FSLSM dimension associated to a particular learning object (active-reflective, visual-verbal, sensing-intuitive, sequential-global). Thus all learning objects have to be classified according to FSLSM in order to allow for delivering of adapted content.

(Brown et al., 2005) proposes a learning style taxonomy, based on Curry's onion model (Curry, 1987). In the LAG adaptation model, each learning style can be associated with a specific instructional strategy, which can be broken down into adaptation language constructs, which in their turn can be represented by elementary adaptation techniques. It is the role of the author to specify not only the annotated learning content (the static description) but also the adaptation logic (the dynamic description).

Finally, (Shi et al., 2004) introduces the concept of Open Learning Objects, which represent distributed multimedia objects in SVG format. They incorporate inner metadata in XML format which is structured on several levels (content, adaptation, animation...). Each Open Learning Object is tied to a particular learning style dimension; however any learning style model can be employed, by configuring the adaptation markup.

In this section we sketched an intelligent way of organizing and indexing the learning resources in WELSA. The next step is to offer teachers an authoring tool to help them create courses conforming to this internal format, which is the subject of our next section.

6.3. Course Authoring in WELSA

Generally, the process of authoring adaptive hypermedia involves several steps (Stash, 2007):

- creating the actual content (which should include alternatives to correspond to various learner needs, in terms of media type, instructional role, difficulty level etc)
- creating the domain model (defining the concepts that are to be taught and the prerequisite relations between them)
- specifying the criteria to be used for adaptation (e.g. learner's knowledge level, goals, learning style)
- creating the adaptation model (defining the adaptation logic).

In case of WELSA, authors only have to create the actual content and annotate it with a predefined set of metadata (provide the static description). The hierarchical and prerequisite relations between concepts are implicitly specified by means of the *isFor*, *inverseIsFor*, *requires*, *isRequiredBy*, *isA*, *inverseIsA* metadata elements. The criteria to be used for adaptation are the learning preferences of the students, as defined in the ULSM. Finally, the adaptation model (the dynamic description) is supplied by the application, in the form of a predefined set of adaptation rules, as depicted in section 6.6.

In order to support the teacher in creating courses conforming to WELSA internal format, we designed an authoring tool, which assists the teacher in the process of assembling and annotating the learning resources; it automatically generates the appropriate file structure, as required by the specific way of organizing and indexing the educational content in WELSA. 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 adding metadata to existing learning resources and defining the course structure (specifying the order of resources, assembling learning objects in pages, subsections and sections).

The editor was implemented as a web-based tool, using JSP and XML technologies (JSP, 2008; XML DOM, 2008), Apache Tomcat 6.0 as application server (Tomcat, 2008) and MySQL 5.0 as DBMS (MySQL, 2008).

The Course Editor at Work

After logging into the system and selecting a course (Fig. 6.8), the teacher is offered the possibility to add, remove or modify existing chapters. Figure 6.9 shows the corresponding page for an Artificial Intelligence course, which currently contains 4 chapters. Next, the teacher can define the structure of a selected chapter, by creating sections and subsections and uploading the actual learning objects, as can be seen in Fig. 6.10. Finally, the metadata files need to be created, by using the supplied metadata editor

(see Fig. 6.11). The corresponding XML files are subsequently generated by the application and stored on the server.



Figure 6.8. A snapshot of the course editor – selecting a course

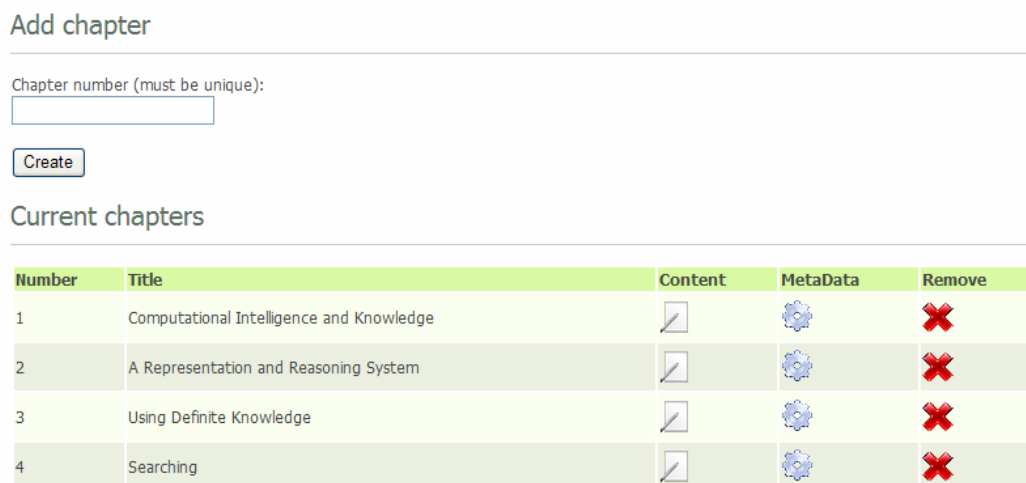


Figure 6.9. A snapshot of the course editor – adding chapters

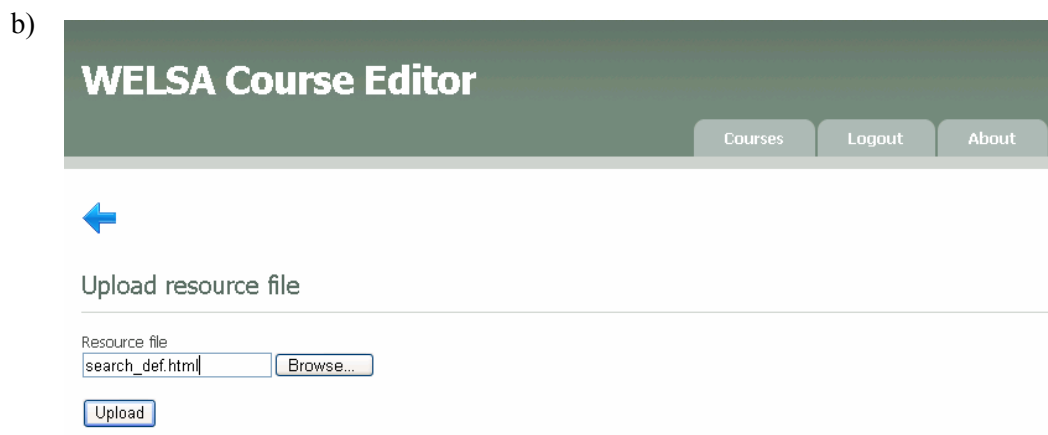
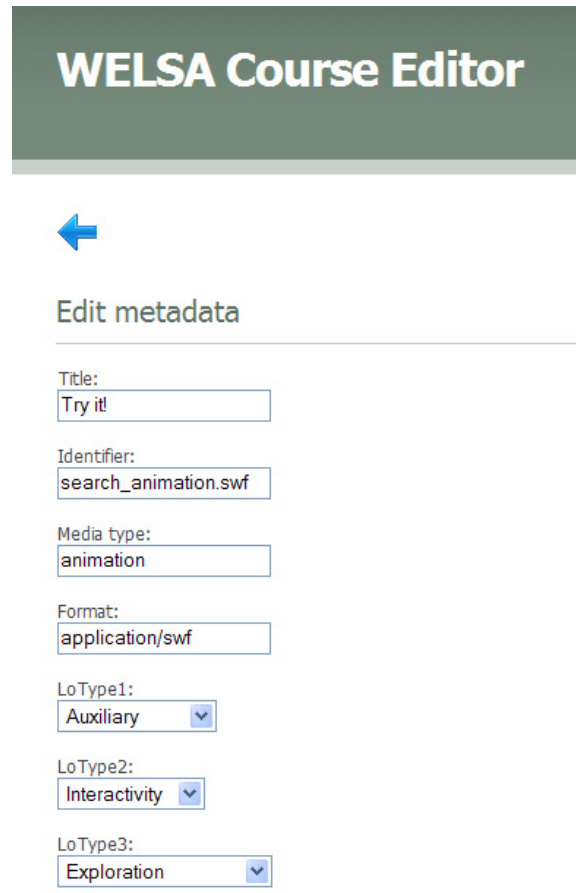


Figure 6.10. A snapshot of the course editor: a) adding/removing learning objects; b) uploading learning objects



The screenshot shows the 'WELSA Course Editor' interface. At the top, there is a dark green header with the text 'WELSA Course Editor' in white. Below the header is a blue left-pointing arrow. The main content area is titled 'Edit metadata' and contains several input fields and dropdown menus. The fields are: 'Title' with the value 'Try it!'; 'Identifier' with the value 'search_animation.swf'; 'Media type' with the value 'animation'; 'Format' with the value 'application/swf'; 'LoType1' with a dropdown menu showing 'Auxiliary'; 'LoType2' with a dropdown menu showing 'Interactivity'; and 'LoType3' with a dropdown menu showing 'Exploration'.

Figure 6.11. A snapshot of the metadata editor

Once the course files are created by the authoring tool, a player is needed in order to generate the HTML files that will be shown to the students. In the next section we describe this course player, which is enhanced with learner tracking capabilities, in order to monitor and record all student actions for further analysis.

6.4. WELSA Course Player

WELSA doesn't store the course web pages but instead generates them on the fly, by means of the course player module. The schematic representation of this component's architecture is illustrated in Fig. 6.12.

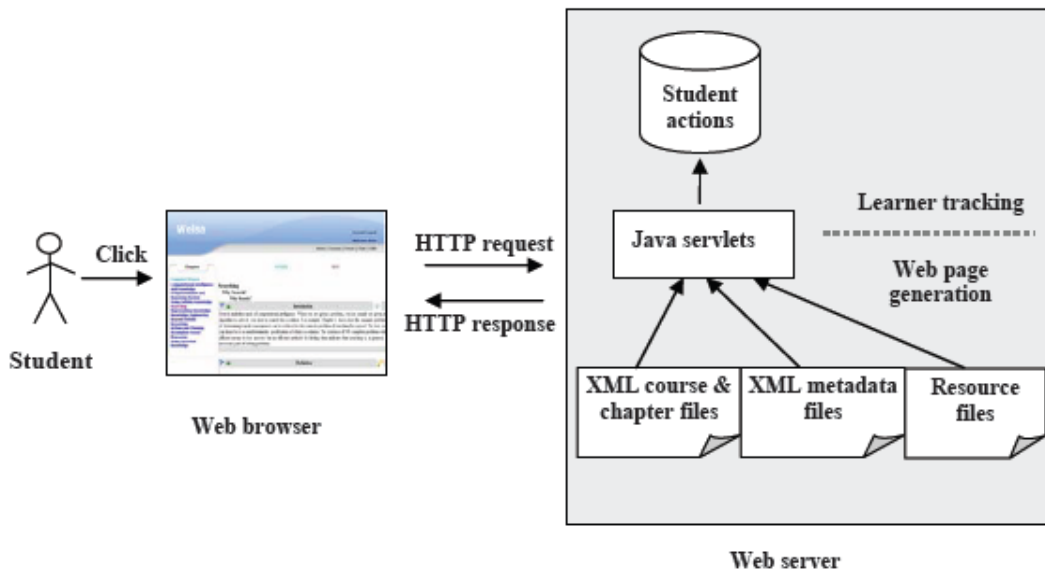


Figure 6.12. Course player schematic architecture

The main function of the course player is to generate the web pages so that they can be visualized by the students. These web pages are dynamically composed from the elementary learning objects, following the structure indicated in the XML course and chapter files (see Fig. 6.4). An example of such a web page resulted from composing several LOs is included in Fig. 6.13.

Another function of the course player is to track student actions (down to click level) and record them in a database for further processing. This is done with the help of JavaScript code added to the HTML page, coupled with Ajax technology (Ajax, 2008). Thus the application can communicate with the web server asynchronously in the background, without interfering with the display and behavior of the existing page. In traditional web applications, the server returns a new page each time the user submits input, so that the application may run more slowly and tend to be less user-friendly. With Ajax, the JavaScript code can communicate directly with the server (through the *XMLHttpRequest* object) and thus a web page can make a request to, and get a response from a web server without reloading the page.

Furthermore, using Ajax, a web application can request only the content that needs to be updated, which drastically reduces bandwidth usage. We therefore use it in WELSA when the student requires the expansion of a learning object, which means that only a small section of the page needs to be reloaded. By using Ajax, WELSA is more responsive, giving users the feeling that changes are happening instantaneously.

As far as the tracking data is concerned, for each student action its author, type, date and a short description are recorded. There are several such action types: *login*, *logout*, *home*, *jumpToCourse*, *jumpToChapter*, *jumpToPage*, *nextButton*, *prevButton*,

outline, *accessLO*, *expandLO*, *collapseLO*, *lockLO*, *unlockLO*. The description differs with the action type, containing specific information, such as the LO identifier in case of an *expandLO* action, or the source and destination page in case of a *jumpToPage* action.

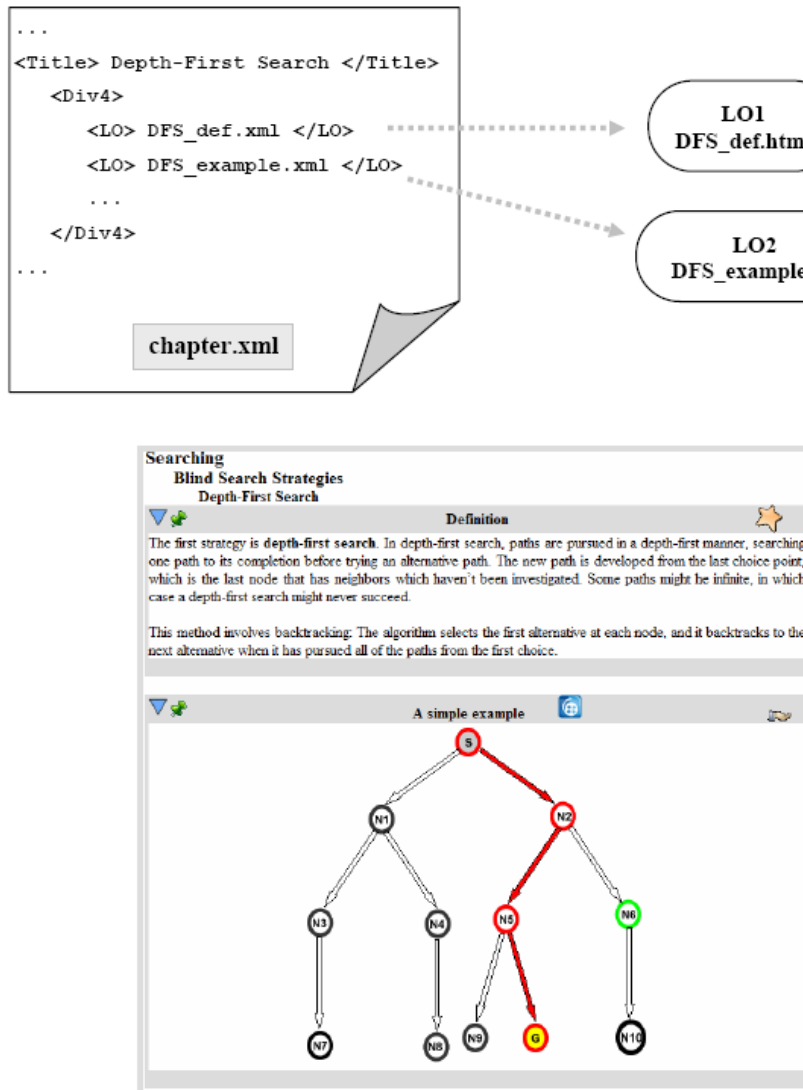


Figure 6.13. Composing a page from elementary learning objects

Using the Course Player

Apart from the two specific functionalities (web page generation and learner monitoring), WELSA course player also incorporates some basic LMS functions, such as: administrative support (registration and authentication) and communication and collaboration tools (discussion forum, chat).

When first accessing WELSA, the student is asked to provide login credentials, as in Fig. 6.14.

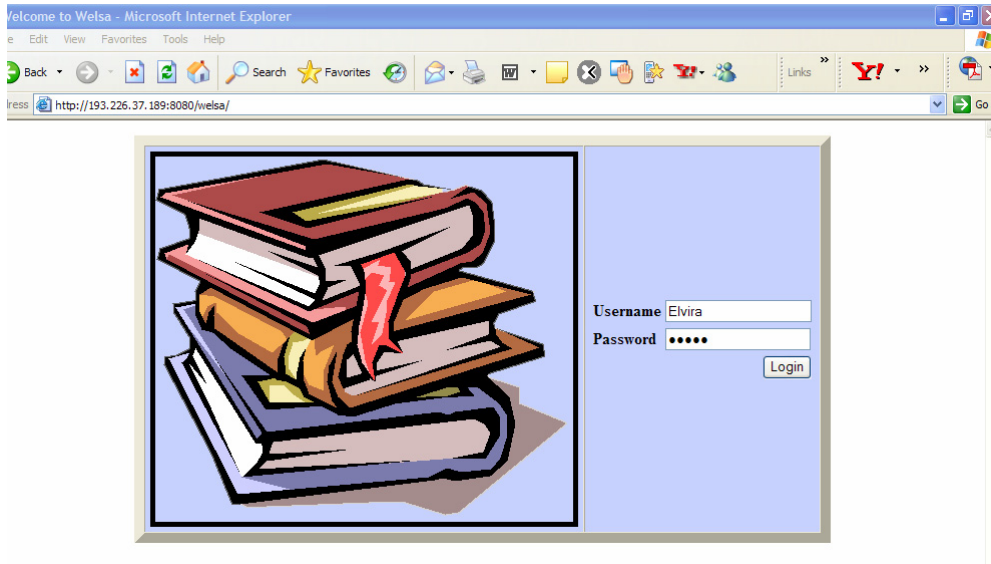


Figure 6.14. WELSA – login page

Next the student may choose between browsing through a course (Fig. 6.15), accessing the chat or visiting the forum (Fig. 6.16).

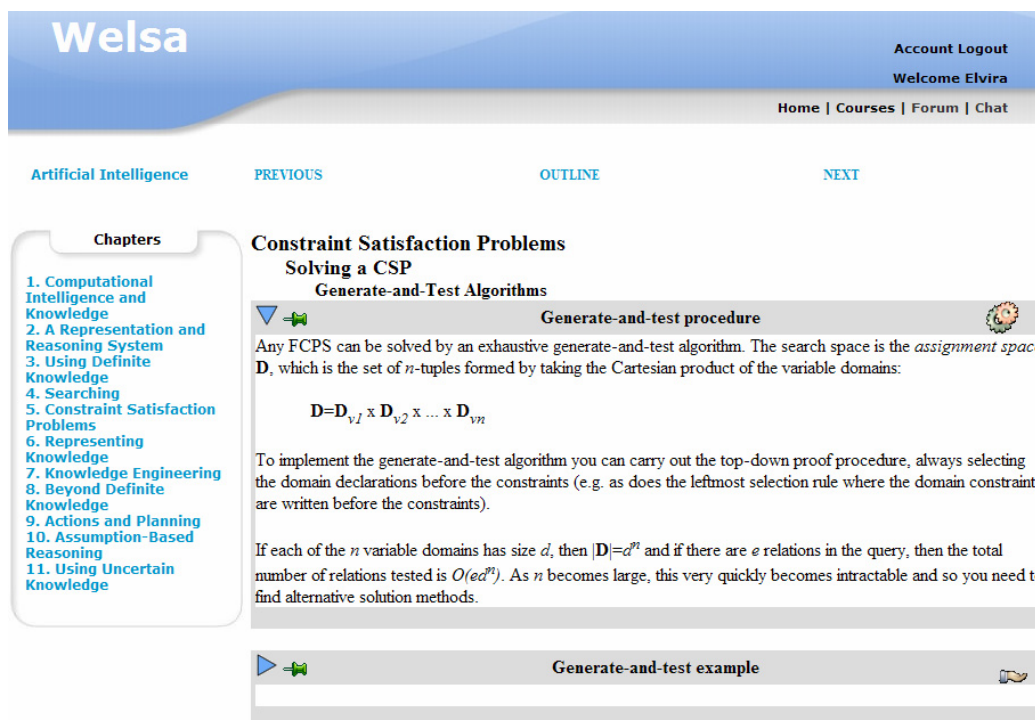


Figure 6.15. WELSA – a snapshot of the course player

The screenshot shows the WELSA Forum interface. At the top, it says "WELSA Forum" and "Hello Elvira" with the date and time "July 15, 2008, 12:04:47 pm". Below this, there are instructions: "Show unread posts since last visit.", "Show new replies to your posts.", and "Total time logged in: 3 minutes." A "News:" section contains a search bar and a "Search" button. A navigation menu includes "HOME", "HELP", "SEARCH", "PROFILE", "MY MESSAGES", "MEMBERS", and "LOGOUT". The main content area is titled "WELSA Forum" and lists two courses: "Artificial Intelligence Course" and "E-Commerce Course".

Artificial Intelligence Course			
	Introduction to AI	2 Posts 1 Topics	Last post by Elvira in Re: What is AI? on Today at 12:01:00 pm
	Using Definite Knowledge	0 Posts 0 Topics	
	Searching	0 Posts 0 Topics	
	Constraint Satisfaction Problems	0 Posts 0 Topics	
	General Discussions	0 Posts 0 Topics	
	Homework Assignments	0 Posts 0 Topics	
E-Commerce Course			
	Introduction to E-Commerce	0 Posts 0 Topics	

At the bottom, there are buttons for "New Posts" and "No New Posts", and a "MARK ALL MESSAGES AS READ" button.

Figure 6.16. WELSA Forum

A few notes should be made regarding the generated web pages: the first resource (LO) on the page is entirely visible (expanded form), while for the rest of LOs only the title is shown (collapsed form). Of course, the student may choose to expand or collapse any resource, as well as locking them in an expanded state by clicking the corresponding icons (and , respectively). Also, there are specific icons associated to each LO, depending on its instructional role and its media type, in order to help the learner browse more effectively through the resources. Finally, navigation can be done by means of the Next and Previous buttons, the course outline or the left panel with the chapter list.

6.5. WELSA Analysis Tool

Once the learner actions are recorded by the course player, they have to be processed by the Analysis tool, in order to yield the learning preferences of the students. The modeling mechanism is depicted in Fig. 6.17.

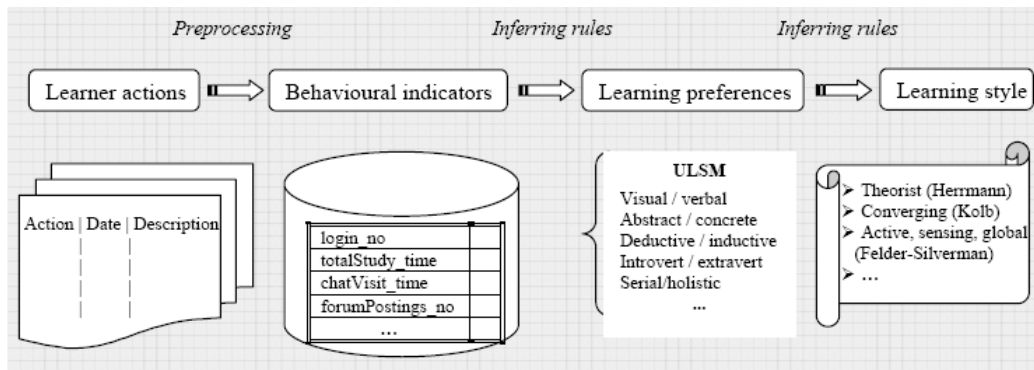


Figure 6.17. WELSA learner modeling mechanism

As we pointed out in section 6.1, the Analysis tool is mainly aimed at the teacher, who can modify the predefined pattern weights and thresholds. Since WELSA is an experimental system, the Analysis tool is also aimed at the researcher, who can visualize the data as well as use them for further analysis. The roles and interactions of the actors with the tool are illustrated in Fig. 6.18.

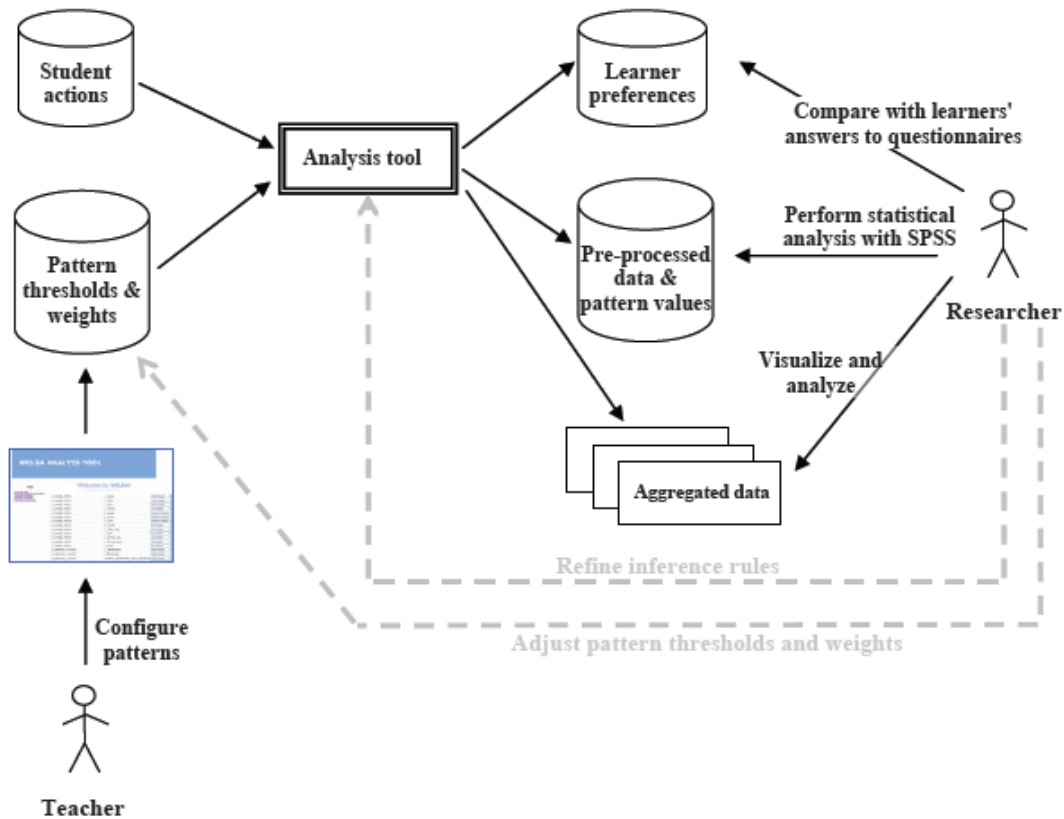


Figure 6.18. Users' interaction with the Analysis tool

The Analysis tool implements the automatic modeling method introduced in Chapter 4. Besides the function of diagnosing the student learning preferences, the Analysis tool also offers various aggregated data that can be used by the researcher for comparisons and statistical purposes. Furthermore, all the intermediate data (duration of learner actions, pattern values, pattern thresholds, reliability and confidence values) can be visualized by the researcher.

In order to compute the pattern values, a pre-processing phase of the raw data (i.e. the student actions and the associated timestamps) is necessary. The first step is to compute the duration of each action for each student, eliminating the erroneous values (for example, accessing the outline for more than 3 minutes means that the student actually did something else during this time). Next the access time for each LO is computed, again filtering the spurious values (for example, an LO access time of less than 3 seconds was considered as random or a step on the way to another LO and therefore not taken into account). The data were then aggregated to obtain the pattern values for each student, as defined in Chapter 4 (e.g. total time spent on the course, total number of actions performed while logged in, time spent on each type of LO, number of hits on each category of LOs, the order of accessing the LOs, the number of navigation actions of a specific type, the number of messages in chat / forum etc). The reliability levels of these patterns are calculated as well.

Next the Analysis tool computes the ULSM preferences values, based on the pattern values, their reliability levels and their weights, using the formulas defined in Chapter 4. The confidence values are also computed, based on the availability of data for each student, and consequently on the reliability levels. Finally, the learner model is updated with the newly identified ULSM preferences.

At teacher's request, the analysis tool also computes and displays aggregated information, such as the total number of students with each ULSM preference, the total and average number of student actions, the average reliability and confidence values etc.

Using the Analysis Tool

After logging into the system, the teacher/researcher can choose between configuring the pattern weights / thresholds, visualizing the learner preferences or various aggregated data, as seen in Fig. 6.19.

Welcome Elvira
Logout

WELSA ANALYSIS TOOL

Compute pattern values
Compute learner preferences
Visualize learner preferences
Compute statistics
Configure weights
Configure thresholds

Welcome to Welsa Analysis tool!

AI Course

Figure 6.19. The main page of the Analysis tool

As explained in Chapter 4, the pattern weights and thresholds depend to a certain extent on the structure and the subject of the course, so the teacher should have 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. This is why the Analysis tool has a configuration option, which allows the teacher to modify the weight and threshold values, as seen in Fig. 6.20.

a)

Compute pattern values
Compute learner preferences
Visualize learner preferences
Compute aggregated data
Configure weights
Configure thresholds

Welcome to Welsa Analysis tool!

AI course

ULSM preference	Associated patterns	Pattern weight
p_visual/p_verbal	t_Image	High Weight
p_visual/p_verbal	t_Video	High Weight
p_visual/p_verbal	t_Text	High Weight
p_visual/p_verbal	t_Sound	No Weight
p_visual/p_verbal	h_Image	Medium Weight
p_visual/p_verbal	h_Video	Medium Weight
p_visual/p_verbal	h_Text	Medium Weight
p_visual/p_verbal	h_Sound	No Weight
p_visual/p_verbal	n_Chat_msg	No Weight
p_visual/p_verbal	t_Chat	No Weight
p_visual/p_verbal	n_Forum_msg	No Weight
p_visual/p_verbal	n_Forum_reads	No Weight
p_visual/p_verbal	t_forum	No Weight
p_abstract/p_concrete	t_Fundamental	High Weight
p_abstract/p_concrete	t_Illustration	High Weight
p_abstract/p_concrete	sequence_fundamental_before_illustration	High Weight
p_abstract/p_concrete	sequence_abstract_first	High Weight
p_abstract/p_concrete	t_Abstract	No Weight

b)

Welcome to Welsa Analysis tool!
AI course

Pattern	Low-Medium Threshold	Medium-High Threshold
grade_abstract	75.0 %	125.0 %
grade_concrete	75.0 %	125.0 %
grade_connections	75.0 %	125.0 %
grade_details	75.0 %	125.0 %
grade_details	75.0 %	125.0 %
grade_overview	75.0 %	125.0 %
h_abstract	75.0 %	125.0 %
h_AdditionalInfo	75.0 %	125.0 %
h_concrete	75.0 %	125.0 %
h_Details	75.0 %	125.0 %
h_Exercise	75.0 %	125.0 %
h_Exploration	75.0 %	125.0 %
h_Image	75.0 %	125.0 %
h_Introduction	75.0 %	125.0 %
h_Objectives	75.0 %	125.0 %

Figure 6.20. Analysis tool – configuration options:
a) Modify weights; b) Modify thresholds

Finally, when the teacher/researcher selects the "Compute learner preferences" option, the rules for computing ULSM preferences are applied on the currently available student data. The results are displayed in Fig. 6.21.

Welcome to Welsa Analysis tool!
AI course

- Compute pattern values
- Compute learner preferences
- Visualize learner preferences
- Compute aggregated data
- Configure weights
- Configure thresholds

Student	ULSM dimension	Preference
Student1	p_visual/p_verbal	p_visual
Student1	p_abstract/p_concrete	p_concrete
Student1	p_serial/p_holistic	p_serial
Student1	p_individual/p_team	p_individual
Student1	p_carefulDetails/p_notCarefulDetails	p_carefulDetails
Student1	p_activeExperimentation/p_reflectiveObservation	p_activeExperimentation
Student2	p_visual/p_verbal	p_visual
Student2	p_serial/p_holistic	p_holistic
Student2	p_abstract/p_concrete	p_abstract

Figure 6.21. A snapshot of the Analysis tool – visualizing the students' ULSM preferences

6.6. WELSA Adaptation Component

The adaptation component consists of a Java servlet which automatically generates the individualized web page, each time an HTTP request is received by the server, as illustrated in Fig. 6.22.

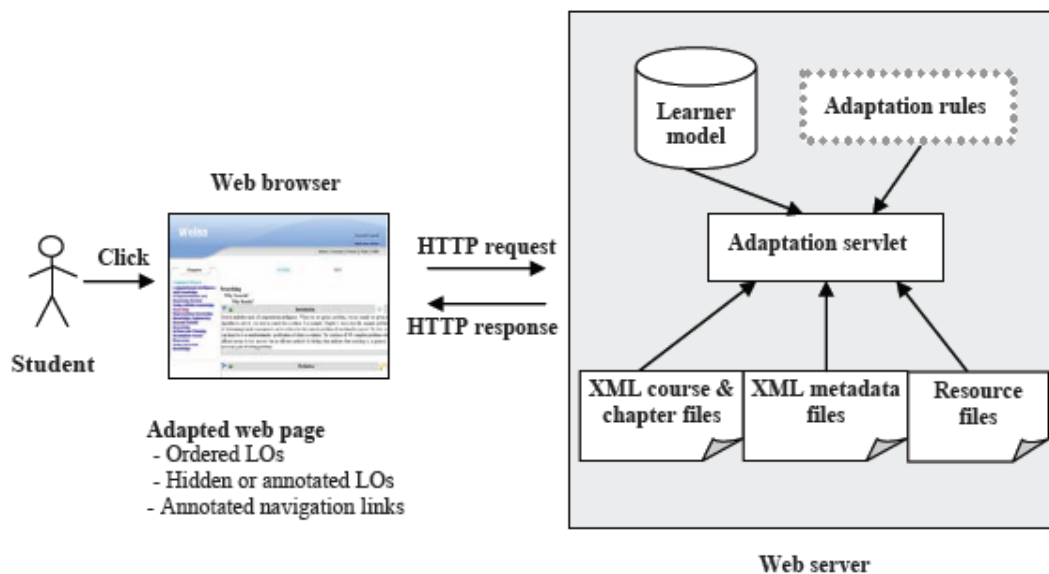


Figure 6.22. Adaptation component schematic architecture

The adaptation servlet queries the learner model database, in order to find the ULSM preferences of the current student. Based on these preferences, the servlet applies the corresponding adaptation rules and generates the new HTML page. These adaptation rules involve the use of LO metadata, which as already stated in section 6.2, 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 composed from the selected and ordered LOs, each with its own status (highlighted, dimmed or standard). This dynamic generation process is illustrated in Fig. 6.23 and Fig. 6.24, for two learners with different ULSM preferences. The relationship between various ULSM dimensions and the adaptive features of the system is thus highlighted.

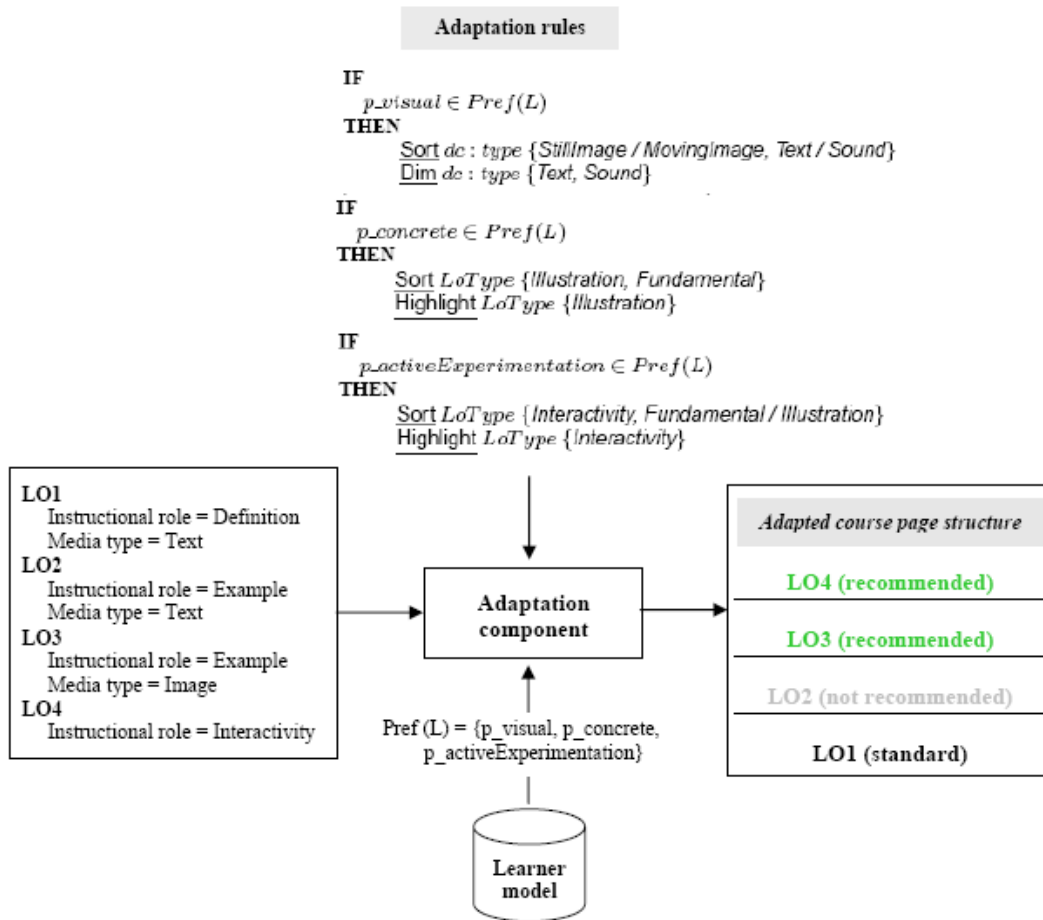


Figure 6.23. Automatic generation of an adapted course page for a student with preferences towards visual perception modality, concrete examples and active experimentation

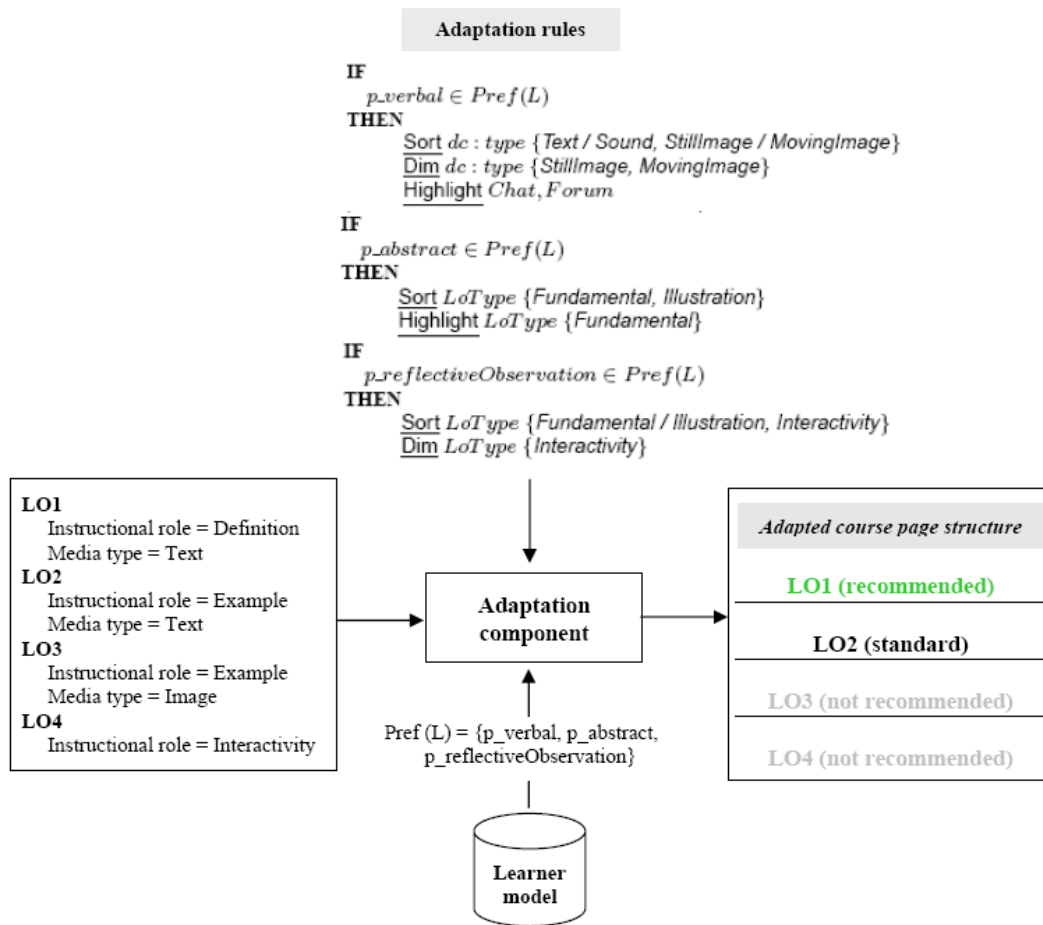


Figure 6.24. Automatic generation of an adapted course page for a student with preferences towards verbal perception modality, abstract examples and reflective observation

The description of the adaptation rules in the above figures and their pedagogical justification were included in Chapter 5. Here we only add a concrete example from WELSA to illustrate the adaptation mechanism (see Fig. 6.25).

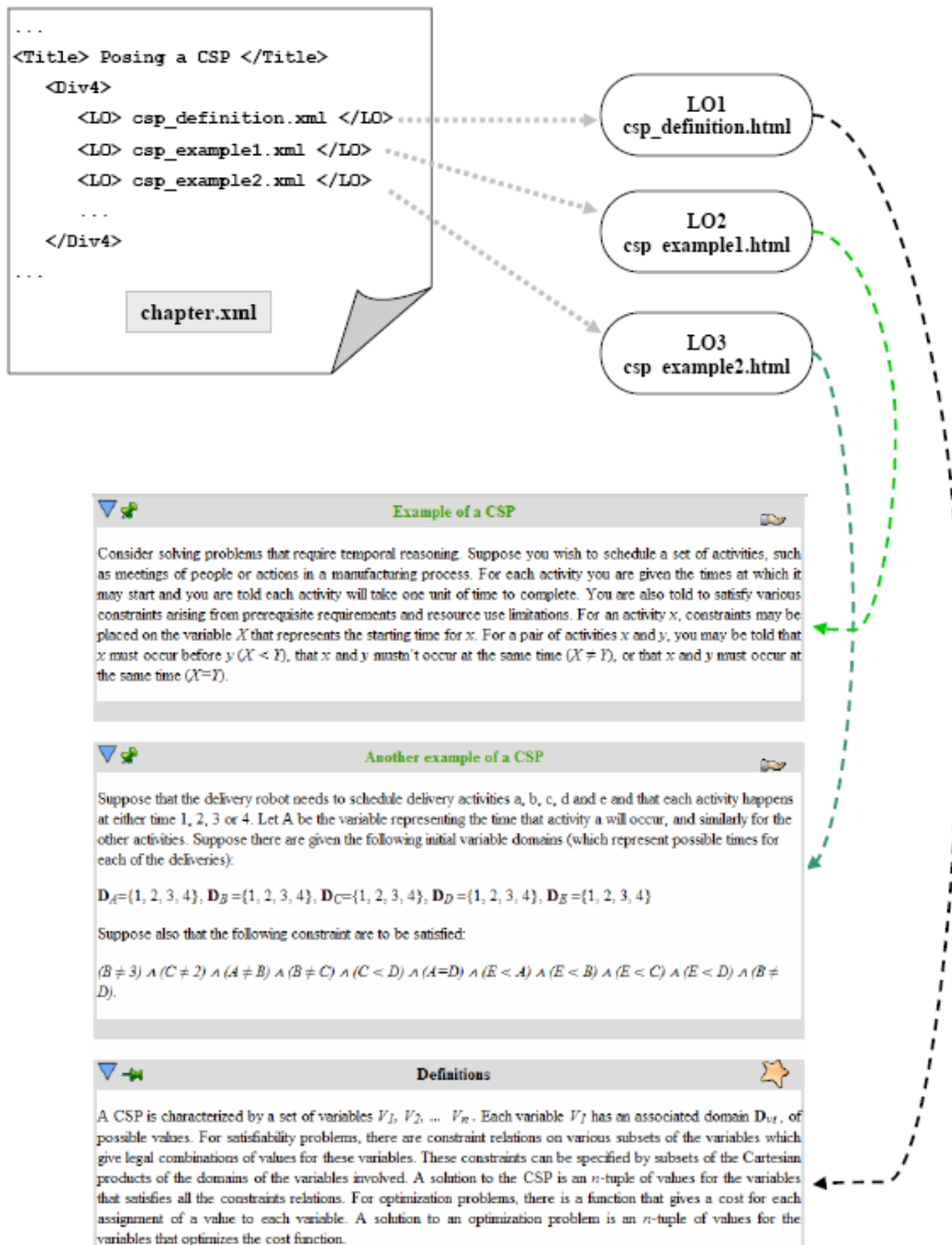


Figure 6.25. Output of WELSA adaptation component for a student with *Concrete* preference

6.7. An Artificial Intelligence Course in WELSA

In order to validate our approach, we implemented a course module in the domain of Artificial Intelligence, based on the chapter dedicated to search strategies and solving problems by search, from the classic textbook of Poole, Mackworth and Goebel (1998). The module consists of 4 sections and 9 subsections, including a total of 46 LOs. The distribution of LOs from the point of view of media type and instructional role is summarized in Table 6.1.

LoType1="Fundamental" 12	LoType1="Auxiliary" 34	dc:type="Text" 35
LoType2="Definition" 5	LoType3="AdditionalInfo" 4	dc:type="StillImage" 1
LoType3="Policy" 7	LoType3="Demonstration" 1	dc:type="MovingImage" 7
	LoType3="Example" 14	dc:type="InteractiveResource" 3
	LoType3="Exercise" 5	
	LoType3="Exploration" 3	
	LoType3="Introduction" 5	
	LoType3="Objectives" 1	
	LoType3="Remark" 1	

Table 6.1. Number of LOs composing the "Searching" chapter

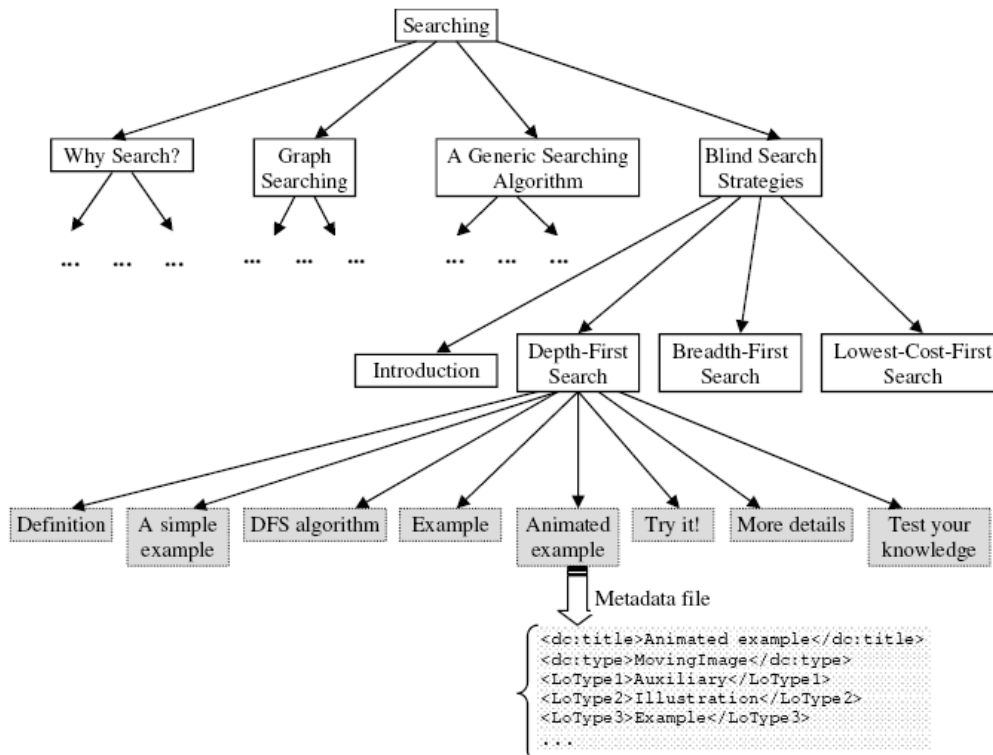


Figure 6.26. AI chapter hierarchical organization (white boxes designate sections and subsections, while grey boxes designate LOs)

The structure of the course chapter is illustrated in Fig.6.26, with a focus on the "Depth-First Search Strategy" subsection.

The corresponding course, chapter and metadata files are included in Fig. 6.27, 6.28 and 6.29 respectively. The XML files follow the structure described in section 6.2.

```

course.xml

<?xml version="1.0" encoding="UTF-8"?>
<course xmlns:p="http://purl.org/dc/elements/1.1/"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xsi:noNamespaceSchemaLocation="course.xsd"
  xsi:schemaLocation="http://purl.org/dc/elements/1.1/
  http://dublincore.org/schemas/xmls/qdc/2006/01/06/dc.xsd ">
  <About>
    <title>Artificial Intelligence</title>
    <identifier>CS104</identifier>
    <creator>Elvira Popescu</creator>
    <date>12-01-2008</date>
    <subject>Artificial Intelligence</subject>
    <description>This is an introductory course on AI</description>
    <language>en</language>
    <source>Computational Intelligence - D. Poole, A. Mackworth, R. Goebel</source>
    ...
  </About>
  <Content>
    <Chapter number="1">Computational Intelligence and Knowledge</Chapter>
    <Chapter number="2">A Representation and Reasoning System</Chapter>
    <Chapter number="3">Using Definite Knowledge</Chapter>
    <Chapter number="4">Searching</Chapter>
    <Chapter number="5">Representing Knowledge</Chapter>
    <Chapter number="6">Knowledge Engineering</Chapter>
    <Chapter number="7">Beyond Definite Knowledge</Chapter>
    <Chapter number="8">Actions and Planning</Chapter>
    <Chapter number="9">Assumption-Based Reasoning</Chapter>
    <Chapter number="10">Using Uncertain Knowledge</Chapter>
  </Content>
</course>

```

Figure 6.27. The XML course file for the Artificial Intelligence course, conforming to the WELSA internal format

```

chapter.xml

<?xml version="1.0" encoding="UTF-8"?>
<Chapter xmlns:dc="http://purl.org/dc/elements/1.1/"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xsi:noNamespaceSchemaLocation="chapter.xsd"
  xsi:schemaLocation="http://purl.org/dc/elements/1.1/
  http://dublincore.org/schemas/xmls/qdc/2006/01/06/dc.xsd ">
  <About>
    <title>Searching</title>
    <creator>Elvira Popescu</creator>
    ...
  </About>
  <Content>
    <Div1>
      <Title>Why Search?</Title>
      <Div2>
        <Title></Title>
        <Div3>
          <Title>Why Search?</Title>
          <Div4>
            <Title></Title>
            <LO>search_introduction.xml </LO>
            <LO>search_def.xml </LO>
            <LO>search_objectives.xml </LO>
          </Div4>
        </Div3>
      </Div2>
    </Div1>
    <Div1>
      <Title>Graph Searching</Title>
      <Div2>
        <Title></Title>
        <Div3>
          <Title>Graph Searching</Title>
          <Div4>
            <Title></Title>
            <LO>graph_search_introduction.xml</LO>
            <LO>graph_search_example.xml</LO>
          </Div4>
        </Div3>
        <Div3>
          <Title>Formalizing Graph Searching</Title>
          <Div4>
            <Title></Title>
            <LO>fgraph_search_definition.xml</LO>
            <LO>fgraph_search_example.xml</LO>
            <LO>test_graph_searching.xml</LO>
          </Div4>
        </Div3>
      </Div2>
    </Div1>
    <Div1>
      <Title>A Generic Searching Algorithm</Title>
      <Div2>
        <Title></Title>
        <Div3>
          <Title>A Generic Searching Algorithm</Title>
          <Div4>
            <Title></Title>
            <LO>generic_search_introduction.xml</LO>
            <LO>generic_search_example1.xml</LO>
            <LO>generic_search_procedure1.xml</LO>
            <LO>generic_search_example2.xml</LO>
            <LO>generic_search_demonstration.xml</LO>
            <LO>generic_search_addinf.xml</LO>
            <LO>generic_search_costs.xml</LO>
          </Div4>
        </Div3>
        <Div3>
          <Title>Finding Paths</Title>

```

```

        <Div4>
            <LO>generic_search_paths_introd.xml</LO>
            <LO>generic_search_paths_procedure.xml</LO>
            <LO>generic_search_paths_example.xml</LO>
            <LO>test_generic_search.xml</LO>
        </Div4>
    </Div3>
</Div2>
</Div1>
<Div1>
    <Title>Blind Search Strategies</Title>
    <Div2>
        <Title></Title>
        <Div3>
            <Title>Blind Search Strategies</Title>
            <Div4>
                <LO> blind_strategies_introduction.xml</LO>
                <LO> tutorial_text.xml</LO>
                <LO> tutorial_video.xml</LO>
            </Div4>
        </Div3>
        <Div3>
            <Title>Depth-First Search</Title>
            <Div4>
                <LO> depth_first_definition.xml</LO>
                <LO> depth_first_simple_example.xml</LO>
                <LO> depth_first_procedure.xml</LO>
                <LO> depth_first_example_txt.xml</LO>
                <LO> depth_first_example_anim.xml</LO>
                <LO> depth_first_example_sim.xml</LO>
                <LO> depth_first_addinf.xml</LO>
                <LO> test_DFS.xml</LO>
            </Div4>
        </Div3>
        <Div3>
            <Title>Breadth-First Search</Title>
            <Div4>
                <LO> breadth_first_definition.xml</LO>
                <LO> breadth_first_simple_example.xml</LO>
                <LO> breadth_first_procedure.xml</LO>
                <LO> breadth_first_example_txt.xml</LO>
                <LO> breadth_first_example_anim.xml</LO>
                <LO> breadth_first_example_sim.xml</LO>
                <LO> breadth_first_addinf.xml</LO>
                <LO> test_BFS.xml</LO>
            </Div4>
        </Div3>
        <Div3>
            <Title>Lowest-Cost-First Search</Title>
            <Div4>
                <LO> lcost_first_definition.xml</LO>
                <LO> lcost_first_simple_example.xml</LO>
                <LO> lcost_first_procedure.xml</LO>
                <LO> lcost_first_example_txt.xml</LO>
                <LO> lcost_first_example_anim.xml</LO>
                <LO> lcost_first_example_sim.xml</LO>
                <LO> lcost_first_addinf.xml</LO>
                <LO> test_LCFS.xml</LO>
            </Div4>
        </Div3>
    </Div2>
</Div1>
</Content>
</Chapter>

```

Figure 6.28. The XML chapter file for the "Searching" chapter

```
depth_first_definition.xml

<?xml version="1.0" encoding="UTF-8"?>
<LO xmlns:dc="http://purl.org/dc/elements/1.1/"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xsi:noNamespaceSchemaLocation="metadata.xsd"
  xsi:schemaLocation="http://purl.org/dc/elements/1.1/
  http://dublincore.org/schemas/xmls/qdc/2006/01/06/dc.xsd ">
  <title>Definition</title>
  <identifier>depth_first_definition.html</identifier>
  <type>text</type>
  <format>text/html</format>
  ...
  <LoType1>Fundamental</LoType1>
  <LoType2>Definition</LoType2>
  <hasAbstractness>neutral</hasAbstractness>
  <hasFormalness>informal</hasFormalness>
</LO>
```

Figure 6.29. The XML metadata file for the "Depth-First Definition" LO

Initially, only the first LO on each page is expanded, the rest being shown in a strechtext format, including only the resource title and some visual cues such as icons for the instructional role and the media type. However, the student has the possibility to expand any LOs on the page and "lock" them in the expanded format. She/he can thus choose between having several LOs available at the same time or concentrating on only one LO at a time. The course also includes access to two communication tools, one synchronous (chat) and one asynchronous (forum) and offers two navigation choices - either by means of the *Next* and *Previous* buttons, or by means of the *Outline*.

Figure 6.30 shows a part of the "Depth-First Search Strategy" subsection, as it is visualized by the end-user (the student), including one LO with *LOType2* = "Definition" and *dc:type* = "Text" and one LO with *LOType3* = "Example" and *dc:type* = "MovingImage", both in an expanded state.

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9. Actions and Planning
10. Assumption-Based Reasoning
11. Using Uncertain Knowledge

Searching

Blind Search Strategies

Depth-First Search

Definition

The first strategy is **depth-first search**. In depth-first search, paths are pursued in a depth-first manner, searching one path to its completion before trying an alternative path. The new path is developed from the last choice point, which is the last node that has neighbors which haven't been investigated. Some paths might be infinite, in which case a depth-first search might never succeed.

This method involves backtracking: The algorithm selects the first alternative at each node, and it backtracks to the next alternative when it has pursued all of the paths from the first choice.

A simple example

Figure 6.30. "Depth-First Search Strategy" subsection

The course was conceived so that a concept is illustrated by various multimedia objects, in order to accommodate different modality perception preferences. For example, the Breadth First Search strategy is explained in textual form (see Fig. 6.31a), as an animated image (see Fig. 6.31b) and by means of an interactive simulation (Fig. 6.31c).

a)

Breadth first search algorithm

To implement breadth-first search you can represent the queue as a list such that the first element of the list is the earliest element of the list. The neighbors are added to the end of the list instead of the beginning as in depth-first search:

```
select(Node, [Node|Frontier], Frontier).
add_to_frontier(Neighbors, Frontier1, Frontier2)←
    append(Frontier1, Neighbors, Frontier2).
```

Notice how we have merely changed the order of arguments to *append* to transform depth-first search into breadth-first search.

Example

Consider breadth-first search on the graph for the delivery robot domain. Initially the frontier is $[o103]$. This is replaced by its neighbors, making the frontier $[ts, l2d3, o109]$. These are the nodes one step away from $o103$. The next three elements of the frontier chosen are ts , $l2d3$ and $o109$, at which stage the frontier contains the neighbors of ts followed by the neighbors of $l2d3$ followed by the neighbors of $o109$, namely

$[mail, l2d1, l2d4, o111, o119]$.

These are the nodes that are two steps away from $o103$. These five nodes are the next elements of the frontier chosen, at which stage the frontier contains the elements three steps away from $o103$, namely

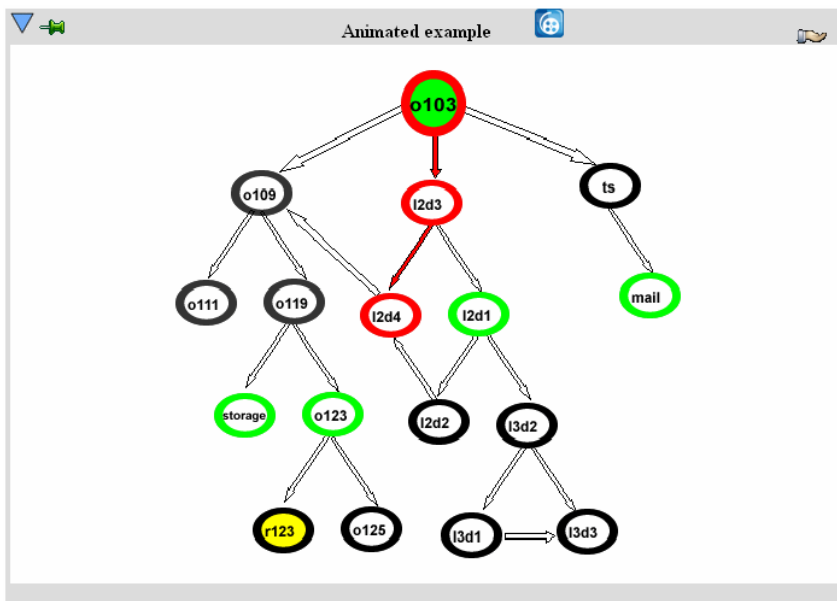
$[l3d2, l2d2, o109, storage, o123]$.

The same frontier for the path-finding search algorithm is

$[node(l3d2, [l2d1, l2d3, o103], 11),$
 $node(l2d2, [l2d1, l2d3, o103], 14),$
 $node(o109, [l2d4, l2d3, o103], 18),$
 $node(storage, [o119, o109, o103], 35),$
 $node(o123, [o119, o109, o103], 37)]$.

Note how each of the paths on the frontier has the same number of steps. For breadth-first search the number of steps in the paths on the frontier always differ by at most one.

b)



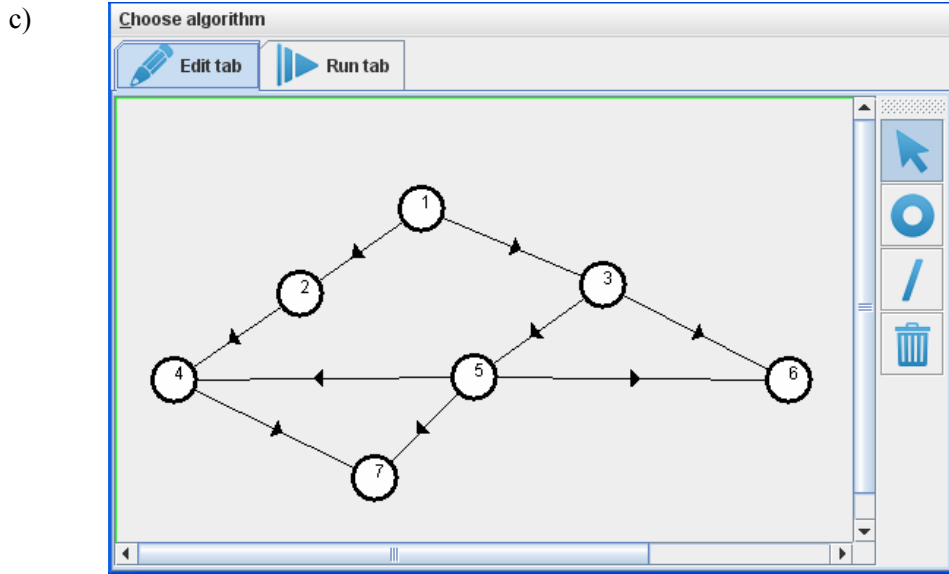


Figure 6.31. Learning objects illustrating Breadth First Search strategy:
 a) *dc:type = Text*, b) *dc:type = MovingImage* c) *dc:type = InteractiveResource*

A similar course module was implemented for the adaptive session. The module deals with Constraint Satisfaction Problems and is based on the same textbook of Poole, Mackworth and Goebel (1998). Figure 6.32 shows a part of the "Consistency Algorithms" subsection, as it is visualized by the student, including one LO with *LOType3 = "Introduction"* and one with *LOType2 = "Definition"*, both having *dc : type = "Text"*.

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Constraint Satisfaction Problems
Solving a CSP
 Consistency Algorithms

Introduction

Although backtracking is usually a substantial improvement over generate-and-test, it still has various inefficiencies that can be overcome. Consider, in the schedule example, variables C and D . The assignment $C=4$ is inconsistent with each of the possible assignments to D since $D_D = \{1, 2, 3, 4\}$ and $C < D$. In the course of the backtrack search this fact can be rediscovered for very many different assignments to A , B and possibly E . This inefficiency can be avoided by simply deleting 4 from D_C , once and for all. This idea is the basis for the consistency algorithm.

Definitions

The consistency algorithms are best thought of as operating over the network of constraints formed by the CSP. Each variable corresponds to a vertex of the graph with its attached domain. Each constraint relation $P(X, Y)$ corresponds to the two arcs and in the graph. Such a network is called a **constraint network**.

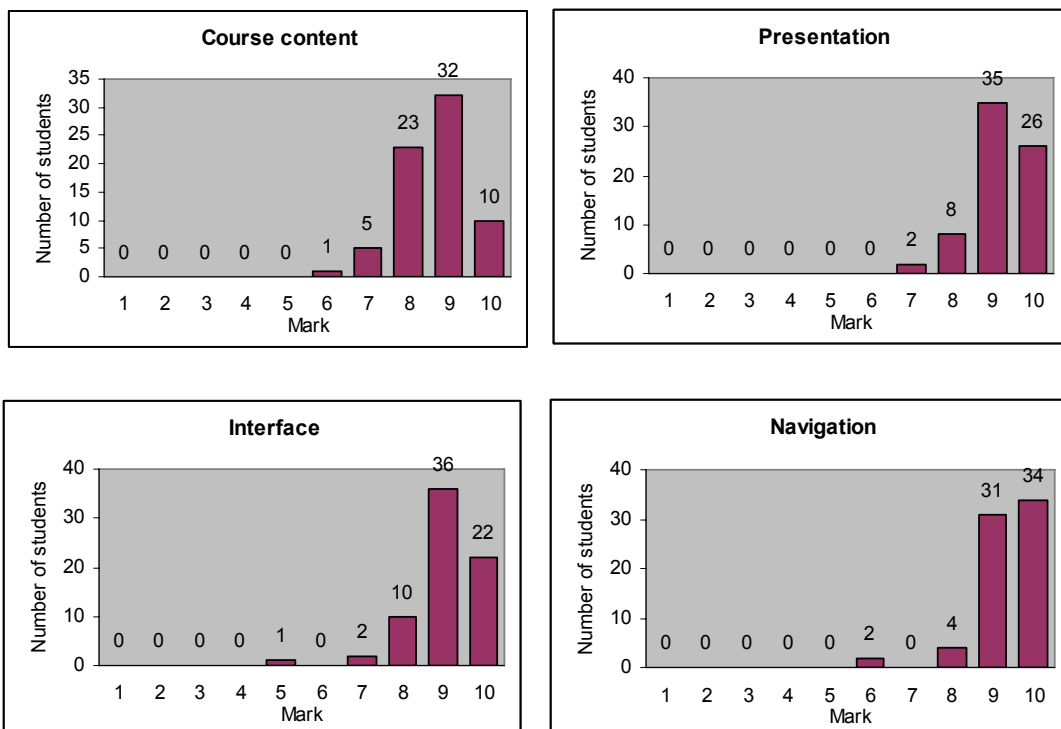
A node in a constraint network is **domain consistent** if no value in the domain of the node is ruled impossible by any of the constraints. Domain consistency doesn't take into account any of the values for any of the other variables.

Figure 6.32. "Consistency algorithms" subsection

6.8. System Validation

The final step of our research was the global evaluation of WELSA system. In order to assess the validity and effectiveness of our system, we used the empirical evaluation approach, involving two experiments with undergraduate students. The settings of the two experiments were described in Chapters 4 and 5 respectively. After interacting with WELSA for a course session, the students were asked to fill in some questionnaires, stating their opinions about the system. The questions related to the effectiveness of the adaptation process and the comparison between the adaptive and non-adaptive versions of the system were addressed in Chapter 5. In what follows we will discuss and analyze the students' answers to those questionnaire items that deal with the WELSA system as a whole and its value as an educational platform.

After the first course session (non-adaptive version), the 71 students who actively participated in the experiment were asked to evaluate various aspects of their learning experience with WELSA system, on a 1 to 10 scale. Thus they had to assess the course content, the presentation, the platform interface, the navigation options, the expand/collapse functionality for the resources, the communication tools and the course as a whole. The results are presented in Fig. 6.33.



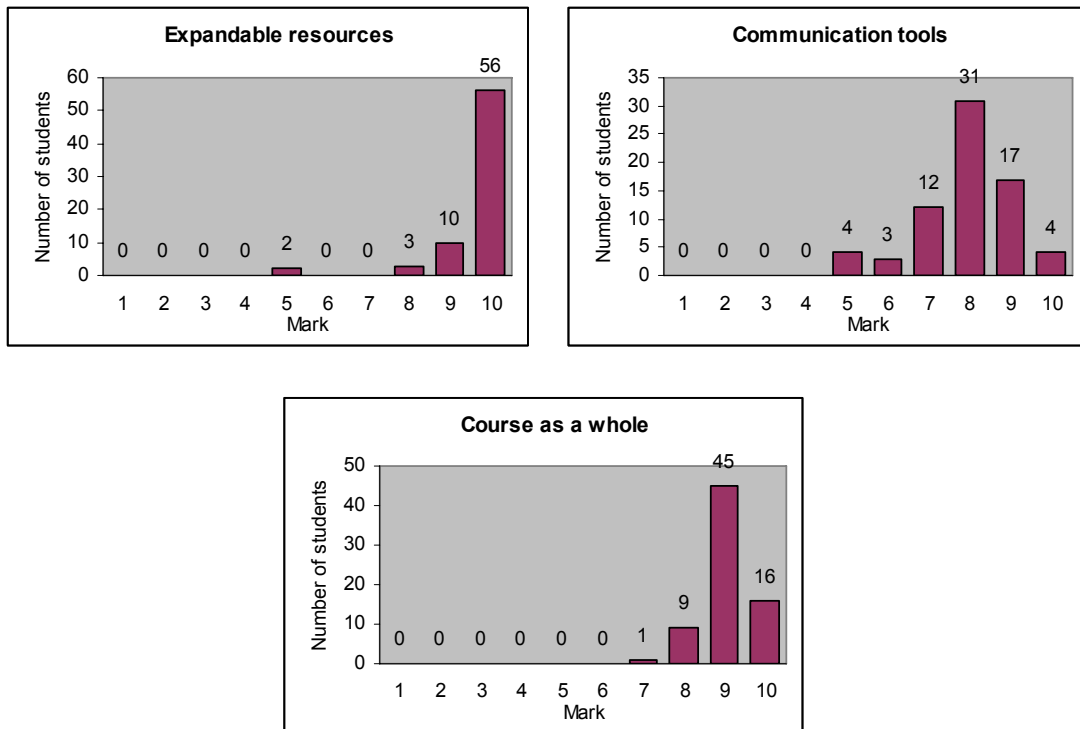


Figure 6.33. Students' assessment of their learning experience with WELSA

As we can see from Fig. 6.33, the students' evaluation of the AI course and WELSA platform is very positive. 59.15% of the students assessed the course content as very good (marks 9-10), 39.44% as good (marks 7-8) and only one student as average. The criticism points were contradictory, some students claiming that the course contained too much theory, while others argued that it should include more details and theoretical aspects. Hence the need for providing individualized courses, in order to respond to the various students' preferences. Furthermore, some students pointed out that there was redundant information ("many examples, in different forms, but illustrating the same thing – it was a bit annoying"). As explained in the previous section, this redundancy was introduced on purpose, in order to offer students the possibility to choose the preferred representation modality. However, the fact that learners considered this as distracting shows once again the necessity of filtering out unnecessary information. Thus providing a variety of resources is not necessarily beneficial, increasing the cognitive overload of the students.

As far as the presentation is concerned, the majority of students (85.92%) found it very enjoyable, ("it was very attractive due to the multitude of animations, images and simulations"), while the rest of 14.08% were also quite pleased with it. Students declared themselves equally satisfied with the course interface, 81.69% of them assigning it marks 9 and 10, 16.90% marks 7 and 8, and only one student describing it as "boring".

Students also appreciated positively the navigation features offered by the system, 91.55% of them giving very high marks (9-10). They were mainly attracted by the course outline, which they considered "a very good idea". The highest marks were obtained by the expandable resource feature (with an average of 9.63) which was appreciated as "original and very useful", "interesting because it allows having both a global view of the course and concentrating on only one fragment". The lowest marks were obtained by the communication tools: the chat was described as "too basic" and the need for more advanced communication tools (audio / video conference, whiteboard) was outlined. Consequently the average mark was only 7.93.

The course as a whole received marks 9-10 from 85.92% of the students, the rest evaluating it as good (marks 7-8).

All in all, very good marks were assigned to most of the features, with only one feature (the communication tools) receiving lower (but still satisfactory) marks. We can therefore conclude that students had a very positive learning experience with WELSA.

We should also mention here WELSA's support for self-regulated learning (SRL). SRL is an important concept in education, being introduced by Zimmerman and Schunk (1989) and subsequently expanded in (Schunk and Zimmerman, 1998; Boekaerts et al., 2000; Perry et al., 2006; Steffens, 2006).

According to (TELEPEERS, 2008), SRL refers to "a set of cross-curricular skills which allow learners to make the most of their learning by being aware of and monitoring the cognitive, motivational, emotional, volitional and social aspects of their learning activities". Indeed, by using WELSA, students become more cognizant of their learning styles and preferences, which helps them more appropriately tackle learning tasks. 73.44% of the 64 students who participated in both experiment sessions reported a substantial increase in their awareness regarding their own strengths and weaknesses in the learning process, as compared to only 10.94% of students who reportedly possessed this self-knowledge before the experiment.

Another important aspect that was evaluated through the questionnaires was the privacy issue: identifying student learning preferences implies the collection of usage data from the students. Learners' willingness to accept the monitoring of their interaction with the system on an everyday basis in exchange for a personalized learning experience was predominant, as can be seen in Fig. 6.34. Thus, 32.39% of the students agreed with the collection of their data in any conditions, 63.38% agreed as long as the data were analyzed in an anonymous fashion and only 4.23% didn't like the idea of their actions being recorded. This is a further proof of the students' need for individualized learning.

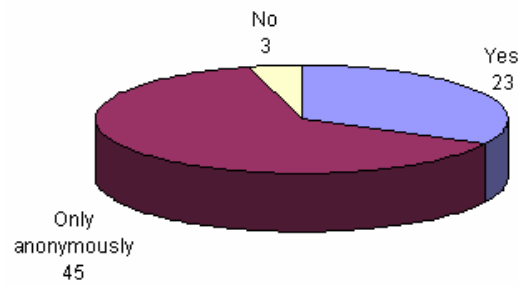


Figure 6.34. Students' opinion on privacy issue: "Would you agree with having your interaction with the system monitored and analyzed?"

The main goal of WELSA system is the provisioning of an adaptive learning experience. Therefore evaluating the adaptive version of the system is of a particular interest. Comparisons between the adaptive and non-adaptive versions as well as between matched and mismatched learners were performed in Chapter 5. Here we are interested in the overall student satisfaction and the desire to use the WELSA system on an everyday basis. We will therefore take into account for our analysis only the 32 students who took part in the matched adaptive course session. The results are summarized in Fig. 6.35 and 6.36.

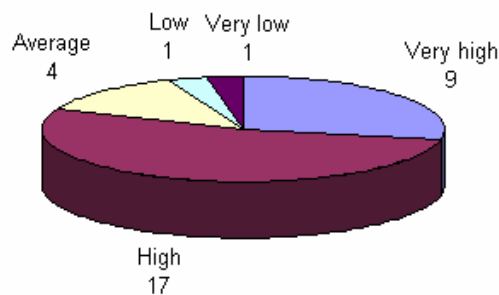


Figure 6.35. Students' overall satisfaction with the adaptive version of the WELSA system

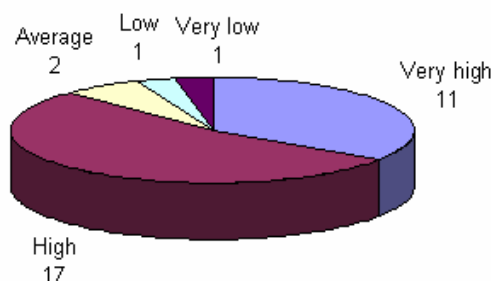


Figure 6.36. Students' willingness to adopt WELSA system for everyday use

As can be seen from the figures, the large majority of the students (81.25%) reported a high or very high degree of satisfaction with WELSA and only 6.25% a low or very low degree. These findings are reflected also in the readiness of the students to adopt WELSA system for large scale use with 87.50% willing to do so and only 6.25% reluctant.

The level of satisfaction offered by the adapted 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. The results are summarized in Fig. 6.37, showing a large majority of the students (90.63%) who perceive learning style adaptation as highly important.

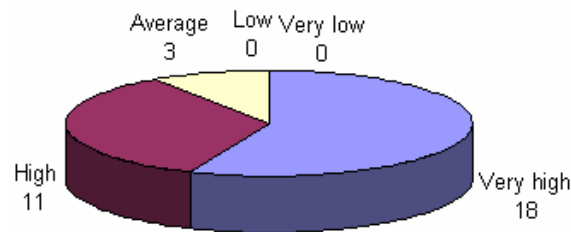


Figure 6.37. Students' perceived importance of learning style adaptation

We can conclude that the overall results of the two experimental studies proved the validity and effectiveness of WELSA system. The analysis of students' answers to the survey instruments supports this claim, revealing the high degree of learner satisfaction with the system.

This chapter addressed the third and last research question, presenting the design, implementation, functionalities, use cases and validation of WELSA adaptive educational system. In the next and final chapter we will summarize the main contributions of this thesis as well as discuss its limitations and the research perspectives that it opens up.

Chapter 7

Conclusions

In this chapter we summarize and discuss the work conducted throughout this thesis. The first subsection reviews the research results obtained and highlights the main contributions. Next, in section 7.2, the limitations of our work are discussed. Finally, section 7.3 points towards future work, identifying further research perspectives.

7.1. Synthesis of Main Results

We started our thesis with a comprehensive literature review, related to adaptive educational hypermedia in general (Chapter 2) and learning style-based adaptation in particular (Chapter 3). Next we tried to answer the 3 main research questions that we asked at the beginning of this thesis; in what follows we will summarize the findings related to each of these questions.

1. What learning style model is most appropriate for use in AEHS and how can learning style be diagnosed?

In Chapter 3 we introduced a Unified Learning Style Model (ULSM), which integrates characteristics from several models proposed in the literature, related to: perception modality, way of processing and organizing information as well as motivational and social aspects. The model was created based on a systematic examination of the constructs that appear in the main learning style models and their intensional definitions. The model presents several advantages: i) it solves the problems related to the multitude of learning style models, the concept overlapping and the correlations between learning style dimensions; ii) it provides a feature-based modeling approach, which is simpler and more accurate than the traditional stereotype-based modeling approach; iii) in turn, this offers the possibility of finer grained and more effective adaptation actions.

Next, in Chapter 4, we showed how these characteristics included in ULSM can be identified from monitoring and analyzing learner behavior in an educational system. First we identified the patterns of behavior that are most indicative of a particular learning preference and confirmed our findings by means of an exploratory study. Next we applied statistical analysis tests to identify significant differences in the patterns of behavior exhibited by students with different ULSM preferences, in the context of a second, larger study. Subsequently, based on these findings as well as on the data collected from the literature, we conceived a rule-based method for diagnosing the ULSM preferences. The approach was validated through experimental research, obtaining good precision results.

Furthermore, once we identified the ULSM learning preferences, we devised a method of using them to categorize the student in one of the traditional learning style models. The applicability of the approach was proved with three of the most popular models, again yielding good precision results.

Hence our main contribution is the proposal of an implicit learner modeling method, based only on the interpretation of students' actions, not requiring any additional effort from the part of the students and bypassing the reliability and validity problems of the existing learning style questionnaires. Furthermore, the approach is not tied to any learning style model, being based on a comprehensive set of learning preferences.

Being able to identify the learning style of the student is an important step, since it can be used to raise students' awareness regarding their strengths and weaknesses in learning as well as give teachers valuable information regarding the learning preferences they should try to accommodate in their courses. In the context of our research, learning style diagnosis is the prerequisite for adaptation provisioning.

2. How can an AEHS perform adaptation according to different learning styles?

In Chapter 5 we identified the adaptation technologies that best serve students with different learning preferences and consequently defined the corresponding adaptation rules. The main achievements of our work are threefold: i) separation of knowledge about learning styles as modularized sets of rules; ii) explicit representation of the rules, encouraging their understandability, maintainability and reusability; iii) facilitation of appropriate implementation of the rules in an adaptive educational hypermedia system. Conceiving these adaptation rules was a delicate task, since it involved interpretation of the teaching guidelines that accompany each of the learning style models, which usually have a descriptive rather than prescriptive character. The adaptation was evaluated experimentally, indicating the positive effect that the matching approach had on learning, as well as the negative effect of mismatching. However these results should be interpreted with caution: the student sample was quite limited and only included students who had little experience with web-based educational systems. 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. From the results of our study we can nevertheless conclude that for the given student sample, the provided adaptation greatly improved perceived learner enjoyment, overall satisfaction, motivation and learning effort.

The study also underlined the importance of using fragment sorting (i.e. resource ordering), one of the simplest adaptive hypermedia techniques, but as it turned out, also one of the most efficient.

3. How can we build a learning style based adaptive educational system and how efficient is it?

In order to answer this question we designed and implemented a dedicated e-learning platform called WELSA (**W**eb-based **E**ducational system with **L**earning **S**tyl **A**daptation), which is described in Chapter 6. The system incorporates the proposed modeling and adaptation methods, proving the applicability of the approaches that we conceived.

Among the main contributions presented in Chapter 6 is the intelligent way of organizing the learning resources and the introduction of a set of educational metadata that are independent of any learning style. We also showed how these metadata can be used to support both modeling the learner and applying various adaptation techniques. Unlike many other AEHS, which are only aimed at students, WELSA also offers support for teachers, by means of the course editor that helps them author courses conforming to WELSA internal format. Another important feature of the system is the Analysis tool, which implements the learner modeling rules, and at the same time offers useful aggregated information to teachers and researchers. Finally, the adaptation component performs a dynamic adaptation, by automatically generating the individualized web pages for each student. Thus the system is able to include a large number of learning preferences, without an increase in the teacher workload; indeed, she/he will have to prepare the same amount of educational materials, which will be dynamically combined by the system, according to each student's preferences.

The validity and efficiency of the system was proved experimentally, the majority of students evaluating their learning experience with WELSA as very positive and highly satisfying.

We can conclude that providing students with a course that is contrary to their learning style may have a hindering effect on learning (in terms of motivation and consequently learning gain). While providing a variety of learning materials, in order to cover all the learning preferences can be a solution, it also increases the cognitive overload of the student, thus not being always recommended. In this case, according to our study, offering the student the course that best matches her/his learning preferences furnishes the best results.

We do not claim to have solved the "wicked problem" of learning style modeling and adaptation. We do however hope to have shed light on some aspects and filled in some of the gaps. Further research is of course needed to clarify the remaining and newly raised issues.

7.2. Limitations

A limitation of this thesis is represented by the relatively restricted student sample that was used in our experiments – in order to allow for generalization, the modeling and adaptation methods should be tested on a wider scale, with users of variable

age, field of study, background knowledge and technical experience. However this is a limitation that most studies in the e-learning area suffer from. Indeed, the number of students in our experiments is greater than the average reported in related work (e.g. 22 in (Bajraktarevic et al., 2003), 64 in (Mitchell et al., 2004), 70 in (Cha et al., 2006a), 27 in (Garcia et al., 2007)).

Furthermore, the laboratory settings could be seen as a limitation. When students know they are observed, the Hawthorne effect (i.e. a short-term improvement caused by observing user performance) might alter their normal behavior (Landsberger, 1958). However, it should be noted that students were not aware of the purpose or expected outcome of the experiment, so it is unlikely that they deliberately tried to confirm researcher's expectations. Nevertheless, it would be interesting to conduct the experiments in more realistic settings, with students working from the privacy of their own homes and for longer periods of time.

7.3. Research Perspectives

As we have already pointed out in the previous section, repeating the experiments for longer periods of time, with a larger number of students with different background and knowledge levels, and in different study domains is a worthwhile research direction. In order to allow for such a large scale use of the system, further improvements could be done to WELSA. The system is currently at prototype stage, being dedicated mainly to research purposes (therefore the Researcher role). It could be extended by adding more tools and functionalities borrowed from LMS, such as: more advanced communication and collaboration tools (as the student surveys suggested), student involvement tools (student portfolio, bookmarks, calendar/schedule, searching facilities, context sensitive help etc). An adaptive assessment component could also be added, following the proposal of (Wen et al., 2007).

Further support could also be provided for the teacher / author: while a dedicated course editor is already included, an import / export facility, allowing for conversion between various course formats and standards (e.g. SCORM, IMS LD etc) would be very helpful. It would allow teachers to use existing courses as they are (perhaps adding some additional metadata), which would provide for greater reuse.

The currently used hierarchical organization of the learning content (the course sequencing) reflects a specific instructional approach of the teacher – it does not provide support for a more complex learning design. Our choice was motivated by the fact that it is the most used learning scenario and it requires the least work from the part of the teacher for transforming from one format (the initial one) to another (the WELSA specific). It is outside the scope of this thesis to deal with various learning scenarios but as future work we could consider analyzing the way learning styles can be used with a

problem-based learning scenario, team project-based learning scenario or Socrates dialogue learning scenario.

Another possible extension could be made to the adaptation component, by incorporating a wider variety of adaptation actions and investigating whether there are some adaptation features that have more impact than others.

A very challenging research direction would be the individualization of the adaptation techniques to the characteristics of the students (knowledge level, technical background, experience with AEHS). Several studies (Brusilovsky, 2003; Brusilovsky et al, 2004) suggest that the student knowledge level as well as her/his previous experience with hypermedia systems may have an influence on the effect of the adaptation technique used. 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.

The modeling component could also be extended to take into account the perturbations introduced by the adaptation on students' actions. Students' behavior in the adapted version could then be used as a valuable feedback on the effect of adaptation. In this context, our research can be seen as the basis for a truly dynamic learner modeling approach.

The findings and results obtained in this thesis open up many research perspectives for the AEHS field in general and LSAES in particular. We believe these future directions to be worthwhile endeavors, since throughout this thesis we showed that we both *can* and *should* use learning styles in adaptive web based educational systems.

Appendix A

XML Schemas for Course, Chapter and Metadata Files

course.xsd

```
<?xml version="1.0" encoding="UTF-8"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema"
  xmlns:dc="http://purl.org/dc/elements/1.1/"
  elementFormDefault="qualified">
  <xs:import namespace="http://purl.org/dc/elements/1.1/"
    schemaLocation="http://dublincore.org/schemas/xmls/qdc/2006/
      01/06/dc.xsd" />
  <xs:complexType name="AboutType">
    <xs:sequence>
      <xs:element ref="dc:title" />
      <xs:element ref="dc:identifier" />
      <xs:element ref="dc:creator" maxOccurs="unbounded" />
      <xs:element ref="dc:date" minOccurs="0" />
      <xs:element ref="dc:subject" minOccurs="0" />
      <xs:element ref="dc:description" minOccurs="0" />
      <xs:element ref="dc:language" minOccurs="0" />
      <xs:element ref="dc:publisher" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:contributor" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:source" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:relation" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:coverage" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:rights" maxOccurs="unbounded" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="ChapterType">
    <xs:simpleContent>
      <xs:extension base="xs:anyURI">
        <xs:attribute name="number" type="xs:integer" />
      </xs:extension>
    </xs:simpleContent>
  </xs:complexType>
  <xs:complexType name="ContentType">
    <xs:sequence>
      <xs:element name="Chapter" type="ChapterType" maxOccurs="20" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="CourseType">
    <xs:sequence>
      <xs:element name="About" type="AboutType" />
      <xs:element name="Content" type="ContentType" />
    </xs:sequence>
  </xs:complexType>
  <xs:element name="course" type="CourseType" />
</xs:schema>
```

chapter.xsd

```

<?xml version="1.0" encoding="UTF-8"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema"
  xmlns:dc="http://purl.org/dc/elements/1.1/"
  elementFormDefault="qualified">
  <xs:import namespace="http://purl.org/dc/elements/1.1/"
    schemaLocation="http://dublincore.org/schemas/xmls/qdc/2006/
      01/06/dc.xsd" />
  <xs:complexType name="AboutType">
    <xs:sequence>
      <xs:element ref="dc:title" />
      <xs:element ref="dc:creator" maxOccurs="unbounded" />
      <xs:element ref="dc:date" minOccurs="0" />
      <xs:element ref="dc:subject" minOccurs="0" />
      <xs:element ref="dc:description" minOccurs="0" />
      <xs:element ref="dc:language" minOccurs="0" />
      <xs:element ref="dc:publisher" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:contributor" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:source" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:relation" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:coverage" minOccurs="0"
        maxOccurs="unbounded" />
      <xs:element ref="dc:rights" maxOccurs="unbounded" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="Div4Type">
    <xs:sequence>
      <xs:element name="Title" type="xs:string" nillable="true" />
      <xs:element name="LO" type="xs:anyURI" maxOccurs="20" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="Div3Type">
    <xs:sequence>
      <xs:element name="Title" type="xs:string" nillable="true" />
      <xs:element name="Div4" type="Div4Type" maxOccurs="10" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="Div2Type">
    <xs:sequence>
      <xs:element name="Title" type="xs:string" nillable="true" />
      <xs:element name="Div3" type="Div3Type" maxOccurs="10" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="Div1Type">
    <xs:sequence>
      <xs:element name="Title" type="xs:string" />
      <xs:element name="Div2" type="Div2Type" maxOccurs="10" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="ContentType">
    <xs:sequence>
      <xs:element name="Div1" type="Div1Type"
        maxOccurs="10" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="ChapterType">
    <xs:sequence>

```

```

        <xs:element name="About" type="AboutType" />
        <xs:element name="Content" type="ContentType" />
    </xs:sequence>
</xs:complexType>
<xs:element name="Chapter" type="ChapterType" />
</xs:schema>

```

metadata.xsd

```

<?xml version="1.0" encoding="UTF-8"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema"
  xmlns:dc="http://purl.org/dc/elements/1.1/"
  elementFormDefault="qualified">
  <xs:import namespace="http://purl.org/dc/elements/1.1/"
    schemaLocation="http://dublincore.org/schemas/xmls/qdc/2006/
      01/06/dc.xsd" />
  <xs:element name="LO">
    <xs:complexType>
      <xs:sequence>
        <xs:element ref="dc:title" minOccurs="0" />
        <xs:element ref="dc:identifier" />
        <xs:element ref="dc:type" />
        <xs:element ref="dc:format" maxOccurs="unbounded" />
        <xs:element ref="dc:creator" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element ref="dc:contributor" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element ref="dc:subject" minOccurs="0" />
        <xs:element ref="dc:description" minOccurs="0" />
        <xs:element ref="dc:date" minOccurs="0" />
        <xs:element ref="dc:language" minOccurs="0" />
        <xs:element ref="dc:publisher" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element ref="dc:source" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element ref="dc:relation" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element ref="dc:coverage" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element ref="dc:rights" minOccurs="0"
          maxOccurs="unbounded" />
        <xs:element name="LoType1">
          <xs:simpleType>
            <xs:restriction base="xs:string">
              <xs:pattern
                value="Fundamental | Auxiliary" />
            </xs:restriction>
          </xs:simpleType>
        </xs:element>
        <xs:element name="LoType2" minOccurs="0">
          <xs:simpleType>
            <xs:restriction base="xs:string">
              <xs:pattern
                value="Definition | Fact | Law | Process |
                  Evidence | Explanation | Illustration |
                  Interactivity" />
            </xs:restriction>
          </xs:simpleType>
        </xs:element>
        <xs:element name="LoType3" minOccurs="0">

```

```

<xs:simpleType>
  <xs:restriction base="xs:string">
    <xs:pattern
      value="LawOfNature | Theorem | Policy |
        Demonstration | Proof | Introduction |
        Conclusion | Remark | Synthesis | Objectives |
        AdditionalInfo | Remark | Example |
        CounterExample | CaseStudy | Exercise |
        Exploration | Invitation | RealWorldProblem"/>
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="LoType4" minOccurs="0">
  <xs:simpleType>
    <xs:restriction base="xs:string">
      <xs:pattern value="Procedure" />
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="hasAbstractness" default="neutral">
  <xs:simpleType>
    <xs:restriction base="xs:string">
      <xs:pattern
        value="abstract | neutral | concrete" />
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="hasFormalness" default="neutral">
  <xs:simpleType>
    <xs:restriction base="xs:string">
      <xs:pattern
        value="formal | neutral | informal" />
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="hasStructure" minOccurs="0">
  <xs:simpleType>
    <xs:restriction base="xs:string">
      <xs:pattern
        value="narrative text | table | list" />
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="hasCompetency" minOccurs="0">
  <xs:simpleType>
    <xs:restriction base="xs:string">
      <xs:pattern
        value="knowledge | comprehension | application |
          analysis | synthesis | evaluation" />
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="hasCompetencyLevel" minOccurs="0">
  <xs:simpleType>
    <xs:restriction base="xs:string">
      <xs:pattern
        value="elementary | multiStep | simpleConceptual
          | complex" />
    </xs:restriction>
  </xs:simpleType>
</xs:element>
<xs:element name="hasTypicalLearningTime"
  type="xs:duration" minOccurs="0" />

```

```
<xs:element name="isFor" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
<xs:element name="inverseIsFor" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
<xs:element name="requires" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
<xs:element name="isRequiredBy" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
<xs:element name="isA" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
<xs:element name="inverseIsA" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
<xs:element name="isAnalogous" type="xs:anyURI"
  minOccurs="0" maxOccurs="unbounded" />
  </xs:sequence>
</xs:complexType>
</xs:element>
</xs:schema>
```

Appendix B

Synthesis of Reported Experiments and Applied Questionnaires

Types of measuring instruments used throughout the experiments:

- Dedicated questionnaires for traditional learning styles: Herrmann Brain Dominance Instrument, Felder-Soloman Index of Learning Styles, Kolb Inventory
- ULSM questionnaire (self-diagnosis of students' learning preferences)
- Opinion questionnaires: A, B, C1, C2

Experiment no. 1

Description: Exploratory study, used to investigate the behavior of students with different learning styles in an EHS

Settings

- *Number of students:* 22
- *Course chapter followed:* "Search strategies and solving problems by search"
- *Duration:* 4 hours (2 hours for following the course + 2 hours for discussions and questionnaires)
- *Applied questionnaires:* HBDI, Felder-Soloman Index of Learning Styles, Kolb Inventory, ULSM, Questionnaire A
- *Goal:* Preliminary analysis of the patterns of behavior exhibited by the students in an EHS and discovering relations with particular learning preferences.

Methodology and results

- *Type of data used:* Traces of students' interaction with WELSA
- *Processing method for the data:* Automatically compute the values of the behavioral patterns by means of the Analysis tool
- *Results:* Graphical representations of values obtained for various behavioral patterns; comparisons of these values between opposite ULSM dimensions
- *Results analysis:* The reported results were in agreement with the intensional definitions of the ULSM dimensions, confirming the fact that behavioral patterns can be put in relation to particular learning preferences of the students.

Section reporting the experiment: 4.2.2.

Experiment no. 2

Description: Main study, used primarily for the learner modeling stage (non-adaptive version of WELSA)

Settings

- *Number of students:* 75
- *Course chapter followed:* "Search strategies and solving problems by search"
- *Duration:* 4 hours (2 hours for following the course + 2 hours for discussions and questionnaires)
- *Applied questionnaires:* HBDI, Felder-Soloman Index of Learning Styles, Kolb Inventory, ULSM, A

The data gathered in this experiment were used for several purposes:

I.

- *Goal:* Identify significant differences in the patterns of behavior exhibited by students with different ULSM preferences

Methodology and results

- *Type of data used:* Traces of students' interaction with WELSA (valid data were recorded only for 71 out of the 75 students involved in the experiment)
- *Processing method for the data:* First we automatically computed the values of the behavioral patterns by means of the Analysis tool. Next we divided the students in two groups, with regard to each of the opposite ULSM preferences and we applied two-tailed t-test or two-tailed u-test on the two groups, depending on the distribution normality (which was checked with the Kolmogorov-Smirnov test). The tests were applied using SPSS software package (SPSS, 2008).
- *Results:* Behavioral patterns for which statistically significant differences were found between the two student groups (Table 4.5)
- *Results analysis:* The experiment showed that students with different ULSM preferences indeed behave differently in an EHS, emphasizing also some relations between these preferences and students' behavioral patterns.

Section reporting the experiment: 4.2.3

II.

- *Goal:* Validate the proposed modeling method

Methodology and results

- *Type of data used:* Traces of students' interaction with WELSA (valid data were recorded only for 71 out of the 75 students involved in the experiment) + students' answers to ULSM questionnaire (self-diagnosis of learner preferences)
- *Processing method for the data:* First we computed the learner preferences based on our modeling method introduced in section 4.3.1 (automatic process by means of the Analysis tool). Next we compared these preferences with those indicated by students' self-diagnosis.
- *Results:* The precision of our modeling method (Table 4.9.)
- *Results analysis:* We obtained very good results for two ULSM dimensions (p_abstract / p_concrete and p_activeExperimentation / p_reflectiveObservation), good results for three ULSM dimensions (p_visual / p_verbal, p_serial / p_holistic, p_carefulDetails / p_notCarefulDetails) and moderate results for one ULSM dimension (p_individual / p_team).

Section reporting the experiment: 4.3.2.

III.

- *Goal:* Validate the correspondence rules between ULSM preferences and traditional learning style models

Methodology and results

- *Type of data used:* Students' answers to ULSM questionnaire (self-diagnosis) + students' answers to HBDI, Felder-Soloman Index of Learning Styles, Kolb Inventory
- *Processing method for the data:* Compute students' learning style based on the correspondence rules introduced in section 4.4.1 and compare them with the learning styles resulted from the dedicated questionnaires (HBDI, Felder-Soloman Index of Learning Styles, Kolb Inventory)
- *Results:* The precision of the correspondence rules (Table 4.11, Table 4.12)
- *Results analysis:* The experimental results obtained are very encouraging (constantly over 70% and with an average higher than 80%), confirming the validity of our approach.

Section reporting the experiment: 4.4.2.

IV.

- *Goal:* Subjective evaluation of WELSA system as a whole

Methodology and results

- *Type of data used:* Students' answers to opinion survey (questionnaire A)
- *Processing method for the data:* Aggregate students' ratings of their learning experience with WELSA system, on the 1 to 10 scale (course content, presentation, platform interface, navigation options, expand/collapse functionality for the resources, communication tools and course as a whole)
 - *Results:* Graphical charts of students' evaluations + discussions and interpretations
 - *Results analysis:* Very good marks were assigned to most of the systems' features, with only one feature (the communication tools) receiving lower (but still satisfactory) marks. We can therefore conclude that students had a very positive learning experience with WELSA.

Section reporting the experiment: 6.8.

Experiment no. 3

Description: Main study, used primarily for the adaptation stage (adaptive version of WELSA)

Settings

- *Number of students:* 64 (all of which had also participated in experiment no. 2), split in two groups: one provided with a matched version of the course ("matched group") and one provided with a mismatched version of the course ("mismatched group"), with respect to students' ULSM preferences. Since we used the same subjects for the adaptive and non-adaptive sessions we were able to perform both an intrasubject and an intersubject comparability study.
 - *Course chapter followed:* "Constraint satisfaction problems"
 - *Duration:* 4 hours (2 hours for following the course + 2 hours for discussions and questionnaires)
 - *Applied questionnaires:* B, C1 (for students in the matched group), C2 (for students in the mismatched group).

The data gathered in this experiment were used for several purposes:

I.

- *Goal:* Objective evaluation of the adaptation approach

Methodology and results

- *Type of data used:* Traces of students' interaction with WELSA
- *Processing method for the data:* First we automatically computed the values of the behavioral patterns by means of the Analysis tool. Next we performed a statistical analysis on the data, 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). The tests were applied using SPSS software package (SPSS, 2008).
- *Results:* Behavioral patterns for which statistically significant differences were found between the two student groups (Table 5.2)
- *Results analysis:* The results obtained are very encouraging: the matched adaptation approach greatly increased the efficiency of the learning process, with a significantly lower amount of time needed for studying and a lower number of randomly accessed resources (lower level of disorientation). The effectiveness of the matched adaptation and its suitability for addressing students' real needs are also reflected in the significantly 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.

Section reporting the experiment: 5.3.2.

II.

- *Goal:* Subjective evaluation of the adaptation approach

Methodology and results

- *Type of data used:* Students' answers to opinion surveys (questionnaires B, C1 / C2)
- *Processing method for the data:* Aggregate students' answers (students' subjective estimation of their behavior in the systems and perceived effectiveness, efficiency and overall satisfaction)
- *Results:* Graphical charts of students' answers + discussions and interpretations
- *Results analysis:* The overall results of the experimental study proved the positive effect that our adaptation to learning styles has on the learning process, in terms of perceived learning gain, enjoyment, study time, learning effort, motivation and overall satisfaction. 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.

Section reporting the experiment: 5.3.3.

III.

- *Goal:* Subjective evaluation of WELSA system as a whole

Methodology and results

- *Type of data used:* Students' answers to opinion surveys (questionnaires B, C1)
 - *Processing method for the data:* Aggregate students' answers
 - *Results:* Graphical charts of students' evaluations + discussions and interpretations
- *Results analysis:* By using WELSA, students became more cognizant of their learning styles and preferences, which helped them more appropriately tackle learning tasks. Learners' willingness to accept the monitoring of their interaction with the system on an everyday basis in exchange for a personalized learning experience was predominant. The large majority of the students reported a high or very high degree of satisfaction with WELSA, findings which are also reflected in the readiness of the students to adopt WELSA system for large scale use.

Section reporting the experiment: 6.8.

Questionnaire A

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

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

Why did you choose to follow this order?

2. Which type of resources did you consider most useful for you? Why?

3. Usually when you learn, in what order do you prefer to access the resources? Why?

4. Please evaluate the course session you just followed on a 1 to 10 scale. Please explain your rating, clearly stating positive and negative aspects.

- a) Course content
- b) Content presentation
- c) Platform interface
- d) Navigation options
- e) Expand / collapse functionality for the resources
- f) Communication tools
- g) Course as a whole

Questionnaire B

1. 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?

Please comment on your answers.

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

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

Why did you choose to follow that order?

3. In general, do you consider it useful to be recommended a learning path, particular resources, an order of accessing the resources or do you prefer to choose them by yourself? Why?

4. Did you find useful the fact that the resources were marked as recommended / less recommended? Yes / No

Why?

5. Did you actually follow these recommendations? How so?

6. After participating in both experiment sessions did you become more aware of your learning styles and your own strengths and weaknesses in the learning process?

- a) Yes, to a great extent
- b) Yes, to a certain extent
- c) No, I was aware beforehand.

Please explain.

7. Would you agree with having your interaction with the system monitored and analyzed?

- a) Yes, under any conditions
- b) Yes, as long as the data are collected and analyzed in an anonymous fashion
- c) No

Questionnaire C1 (matched course)

1. To which extent do you believe the course matched your real learning preferences?

Very large / Large / Moderate / Small / Very small

Please explain your answer.

2. To which extent was this adaptation useful for you?

Very large / Large / Moderate / Small / Very small

Please explain your answer.

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

Very high / High / Average / Low / Very low

Please explain your answer.

4. Would you like to use WELSA on an everyday basis?

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

Please explain your answer.

5. 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

Please explain your answer.

Questionnaire C2 (mismatched course)

1. To which extent do you believe the course was contrary to your real learning preferences?

Very large / Large / Moderate / Small / Very small

Please explain your answer.

2. To which extent was this adaptation disturbing for you?

Very large / Large / Moderate / Small / Very small

Please explain your answer.

3. To which extent was this adaptation motivating for you?

Very large / Large / Moderate / Small / Very small

Please explain your answer.

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

Very high / High / Average / Low / Very low

Please explain your answer.

5. Would you like to use WELSA on an everyday basis?

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

Please explain your answer.

6. 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

Please explain your answer.

References

- H. S. Al-Khalifa, H. C. Davis (2006). The Evolution of Metadata from Standards to Semantics in E-Learning Applications. *Proceedings of Hypertext'06*, Odense, Denmark.
- C. Allinson, J. Hayes (1996). The Cognitive Style Index. *Journal of Management Studies*, 33, pp. 119–135.
- C. M. Alonso, D. J. Gallego, P. Honey (2002). *The Learning Styles*. Ediciones Mensajero.
- S. R. Alpert, M. K. Singley, P. G. Fairweather (1999). Deploying Intelligent Tutors on the Web: An Architecture and an Example. *International Journal of Artificial Intelligence in Education*, 10, pp. 183-197.
- J.R. Anderson, S. Douglass, Y. Qin (2004). How Should a Theory of Learning and Cognition Inform Instruction?. *Experimental cognitive psychology and its applications*, American Psychological Association, Washinton D.C.
- L. Anido, M. Fernandez, M. Caeiro, J. Santos, J. Rodriguez, M. Llamas (2002). Educational Metadata and Brokerage for Learning Resources. *Computers and Education*, Elsevier, 38, pp. 351-374.
- M. J. Apter (2001). *Motivational Styles in Everyday Life: a Guide to Reversal Theory*. Washington DC: American Psychological Association.
- L. Aroyo, D. Dicheva (2003). AIMS: Learning and Teaching Support for WWW-based Education. *International Journal for Continuing Engineering Education and Life-Long Learning*, 11 (1/2), pp. 152-164.
- N. Bajraktarevic, W. Hall, P. Fullick (2003). Incorporating Learning Styles in Hypermedia Environment: Empirical Evaluation. *Proc. Workshop on Adaptive Hypermedia and Adaptive Web-Based Systems*, pp. 41-52.
- P. Barker (2005). What is IEEE Learning Object Metadata (the LOM) / IMS Learning Resource Meta-data?. CETIS, <http://metadata.cetis.ac.uk/guides/WhatIsLOM.pdf>
- T. Barker, S. Jones, C. Britton, D. Messer (2000). The Use of the Verbaliser-Imager Cognitive Style as a Descriptor in a Student Model of Learner Characteristics in a Multimedia Application. *Proc. 5th Annual Conference of the European Learning Styles Information Network (ELSIN)*, University of Hertfordshire, UK.
- A. J. Berlanga, F. J. Garcia (2005). Using IMS LD for Characterizing Techniques and Rules in Adaptive Educational Hypermedia Systems. *Current Research on IMS Learning Design – Proc. of the UNFOLD-PROLEARN Joint Workshop*, Valkenburg, pp. 61-80.
- J.J. Beshuizen, E.T. Stoutjesdijk (1999). Study Strategies in a Computer Assisted Study Environment. *Learning and Instruction*, 9, pp. 281–301.

- J. Biggs (1987). *Student Approaches to Learning and Studying*. Australian Council for Educational Research, Hawthorn.
- M. Boekaerts, P. R. Pintrich, M. Zeidner (2000). *Handbook of Self-regulation*. San Diego, CA: Academic Press.
- A. Bork (2001). Tutorial Learning for the New Century. *Journal of Science Education and Technology*, 10 (1), pp. 57-71.
- J. G. Boticario, E. Gaudioso, F. Hernandez (2000). Adaptive Navigation Support and Adaptive Collaboration Support in WebDL. *Proc. Intl. Conf. on Adaptive Hypermedia and Adaptive Web-based Systems (AH2000)*, Springer.
- J.G. Boticario, O.C. Santos, P. van Rosmalen (2005). Issues in Developing Standard-based Adaptive Learning Management Systems. *EADTU 2005 Working Conference: Towards Lisbon 2010: Collaboration for Innovative Content in Lifelong Open and Flexible Learning*.
- J.S. Brown, R.R. Burton, F. Zdybel (1973). A Model-Driven Question-Answering System for Mixed Initiative Computer-Assisted Instruction. *IEEE Transactions on Systems, Man and Cybernetics*, 3(1), pp. 248-257.
- J.S. Brown, R.R. Burton (1978). Diagnostic Models for Procedural Bugs in Basic Mathematical Skills. *Cognitive Science*, 2, pp. 155-192.
- E. Brown, A. Cristea, C. Stewart, T. Brailsford (2005). Patterns in Authoring of Adaptive Educational Hypermedia: A Taxonomy of Learning Styles. *Educational Technology and Society*, 8, pp. 77-90.
- E. Brown, T. Brailsford, T. Fisher, A. Moore, H. Ashman (2006). Reappraising Cognitive Styles in Adaptive Web Applications, *Proc. WWW 2006*, May 23-26, 2006, pp. 327-335.
- E. Brown, T. Fisher, T. Brailsford (2007). Real Users, Real Results: Examining the Limitations of Learning Styles within AEH. *Proc. 18th Conference on Hypertext and Hypermedia (HT '07)*, ACM, New York, NY, pp. 57-66.
- P. Brusilovsky (1994). The Construction and Application of Student Models in Intelligent Tutoring Systems. *Journal of Computer and Systems Sciences International*, 32 (1).
- P. Brusilovsky (1996). Methods and Techniques of Adaptive Hypermedia. *User Modeling and User-Adapted Interaction*, 6(2-3), pp. 87-129.
- P. Brusilovsky, E. Schwarz, G. Weber (1996). A tool for developing adaptive electronic textbooks on WWW. *Proc. WebNet'96, World Conference of the Web Society*, pp. 64-69.
- P. Brusilovsky (1997). Efficient Techniques for Adaptive Hypermedia. In C. Nicholas and J. Mayfield (eds.): *Intelligent hypertext: Advanced techniques for the World Wide Web*, Lecture Notes in Computer Science, Vol. 1326, Berlin: Springer-Verlag, pp. 12-30.

- P. Brusilovsky (1998). Methods and Techniques of Adaptive Hypermedia. In P. Brusilovsky, A. Kobsa and J. Vassileva (eds.): *Adaptive Hypertext and Hypermedia*. Dordrecht: Kluwer Academic Publishers, pp. 1-43.
- P. Brusilovsky, J. Eklund, E. Schwarz (1998). Web-based Education for All: A Tool for Developing Adaptive Courseware. *Proc. 7th International World Wide Web Conference*.
- P. Brusilovsky (2001). Adaptive Hypermedia. *User Modeling and User-Adapted Interaction*, vol. 11, pp. 87-110.
- P. Brusilovsky, H. Nijhavan (2002). A Framework for Adaptive E-Learning Based on Distributed Re-usable Learning Activities. *Proc. World Conference on E-Learning in Corp., Govt., Health., & Higher Ed. 2002*, pp. 154-161.
- P. Brusilovsky, R. Rizzo (2002). Map-based Horizontal Navigation in Educational Hypertext. *Journal of Digital Information*, 3 (1).
- P. Brusilovsky (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), pp. 487-497.
- P. Brusilovsky, C. Peylo (2003). Adaptive and Intelligent Web-based Educational Systems. *International Journal of Artificial Intelligence in Education*, 13 (2-4), pp. 159-172.
- P. Brusilovsky, G. Chavan (2003). Knowledge Sea II. University of Pittsburgh, <http://www.pitt.sis.edu/~taler/KnowledgeSea.html>
- P. Brusilovsky (2004). Adaptive Navigation Support: from Adaptive Hypermedia to the Adaptive Web and Beyond. *PsychNology Journal*, Vol. 2, No. 1, pp. 7-23.
- P. Brusilovsky, C. Karagiannidis, D. Sampson (2004). Layered Evaluation of Adaptive Learning Systems. *International Journal for Continuing Engineering Education and Life-Long Learning*, Vol. 14, Nos. 4/5, pp. 402-421.
- P. Brusilovsky (2007). Adaptive Navigation Support. In P. Brusilovsky, A. Kobsa and W. Neidl (eds.): *The Adaptive Web: Methods and Strategies of Web Personalization*. Lecture Notes in Computer Science, Vol. 4321, Springer, pp. 263-290.
- P. Brusilovsky, E. Millan (2007). User Models for Adaptive Hypermedia and Adaptive Educational Systems. In P. Brusilovsky, A. Kobsa and W. Neidl (eds.): *The Adaptive Web: Methods and Strategies of Web Personalization*. Lecture Notes in Computer Science, Vol. 4321, Springer, pp. 3-53.
- M. Cannataro, A. Cuzzocrea, C. Mastroianni, R. Ortale, A. Pugliese (2002). Modeling Adaptive Hypermedia with an Object-Oriented Approach and XML. *Proc. Second International Workshop on Web Dynamics (WebDyn'02)*, Honolulu, Hawaii.
- J.R. Carbonell (1970). AI in CAI: An Artificial Intelligence Approach to Computer Aided Instruction. *IEEE Transactions on Man-Machine Systems*, 11(4), pp. 190-202.

- R.M. Carro, E. Pulido, P. Rodriguez (2001). TANGOW: A Model for Internet Based Learning. *Journal of Continuing Engineering Education and Life-Long Learning. Special issue on Internet based learning and the future of education*, vol. 11, no 1-2.
- C. A. Carver, R. A. Howard, W. D. Lane (1999). Enhancing Student Learning through Hypermedia Courseware and Incorporation of Student Learning Styles. *IEEE Transactions on Education*, 42, pp. 33–38.
- S. Cassidy (2003). Learning Styles: An Overview of Theories, Models and Measures. *Bridging theory and practice. Proc. Eighth Annual European Learning Styles Information Network Conference*, University of Hull, pp. 80–102.
- S. Ceri, P. Fraternali, A. Bongio (2000). Web Modeling Language (WebML): a Modeling Language for Designing Web Sites. *Computer Networks*, 33(1-6), pp. 137-157.
- H. J. Cha, Y. S. Kim, S. H. Park, T. B. Yoon, Y. M. Jung, J. H. Lee (2006a). Learning Styles Diagnosis Based on User Interface Behaviors for the Customization of Learning Interfaces in an Intelligent Tutoring System. *Proc. ITS 06*, Springer.
- H. J. Cha, Y. S. Kim, J. H. Lee S., T. B. Yoon (2006b). An Adaptive Learning System with Learning Style Diagnosis based on Interface Behaviors. *Workshop Proceedings of International Conference on E-Learning and Games*, April 17-19, 2006, Hangzhou, China.
- T. W. Chan, A. B. Baskin (1990). Learning Companion Systems. *Intelligent Tutoring Systems: At the crossroads of artificial intelligence and education*, Norwood: Ablex Publishing, pp. 6-33.
- F. Coffield, D. Moseley, E. Hall, K. Ecclestone (2004a). *Learning Styles and Pedagogy in Post-16 Learning. A Systematic and Critical Review*. Learning and Skills Research Centre, UK.
- F. Coffield, D. Moseley, E. Hall, K. Ecclestone (2004b). *Should We Be Using Learning Styles? What Research Has to Say to Practice*. Learning and Skills Research Centre, UK.
- O. Conlan, V. Wade, C. Bruen, M. Gargan (2002). Multi-Model, Metadata-Driven Approach to Adaptive Hypermedia Services for Personalized e-Learning. *Proc. Second International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems (AH'2002)*, Málaga, Spain, pp. 100-111.
- M. A. Constantino Gonzalez, D. Suthers, J.G. Escamilla De Los Santos (2003). Coaching Web-based Collaborative Learning Based on Problem Solution Differences and Participation. *International Journal of Artificial Intelligence in Education*, 13 (2-4), pp. 261-297.
- A. Cristea (2003). Adaptive Patterns in Authoring of Educational Adaptive Hypermedia. *Educational Technology & Society*, 6 (4), pp. 1-5.
- A. Cristea, L. Calvi (2003). The Three Layers of Adaptation Granularity. *Proc. User Modeling Conference*, pp. 4-14.

- A. Cristea, A. De Mooij (2003). LAOS: Layered WWW AHS Authoring Model and Its Corresponding Algebraic Operators. *Proc. 14th international World Wide Web conference (WWW2003), Alternate Education track*, Budapest, Hungary.
- A. Cristea (2004). What can the Semantic Web do for Adaptive Educational Hypermedia? *Educational Technology & Society*, 7 (4), pp. 40-58.
- L. Curry (1983). An Organisation of Learning Styles Theory and Constructs. Annual Meeting of the American Educational Research Association, Montreal, Quebec.
- L. Curry (1987). *Integrating Concepts of Cognitive or Learning Style: A Review with Attention to Psychometric Standards*. Ottawa, ON: Canadian College of Health Service Executives.
- D. Dagger, O. Conlan, V.Wade (2003). An Architecture for Candidacy in Adaptive eLearning Systems to Facilitate the Reuse of Learning Resources. *Proc. World Conference on E-Learning in Corporate, Government, Healthcare and Higher Education E-Learn 2003*, Phoenix, Arizona, USA, pp. 49-56.
- P. De Bra, G.J. Houben, H. Wu (1999). AHAM: A Dexter-based Reference Model for Adaptive Hypermedia Applications. *Proc. 10th ACM Conference on Hypertext and Hypermedia*, pp. 147-156.
- P. De Bra, A. Aerts, G. J. Houben, H. Wu (2000). Making General-Purpose Adaptive Hypermedia Work. *Proc. AACE WebNet 2000 Conference*, pp. 117-123.
- P. De Bra, A. Aerts, D. Smits, N. Stash (2002). AHA! Version 2.0, More Adaptation Flexibility for Authors. *Proc. AACE ELearn'2002 Conference*, pp. 240-246.
- P. De Bra, A. Aerts, B. Berden, B. De Lange, B. Rousseau, T. Santic, D. Smits, N. Stash (2003). AHA! The Adaptive Hypermedia Architecture. *Proc. ACM Hypertext Conference*, Nottingham, UK.
- P. De Bra, L. Aroyo, A. Cristea (2004). Adaptive Web-based Educational Hypermedia. In M. Levene, A. Poulouvassilis (eds.): *Web Dynamics. Adapting to Change in Content, Size, Topology and Use*, Springer, pp. 387-410.
- P. De Bra, D. Smits, N. Stash (2006). The Design of AHA!. *Proc. ACM Conference on Hypertext and Hypermedia*, Odense, Denmark.
- S.J. Derry, M.K. Potts (1998). How Tutors Model Students: A Study of Personal Constructs in Adaptive Tutoring. *American Educational Research Journal*, 35 (1), pp. 65-99.
- V. Devedzic (2006). *Semantic Web and Education*, Springer.
- P. Dolog, N. Henze, W. Nejdl, M. Sintek (2004). Personalization in Distributed eLearning Environments. *Proc. Intl. Conf. WWW2004*.

- P. Dolog, W. Nejdl (2007). Semantic Web Technologies for the Adaptive Web. In P. Brusilovsky, A. Kobsa and W. Neidl (eds.): *The Adaptive Web: Methods and Strategies of Web Personalization*. Lecture Notes in Computer Science, Vol. 4321, Springer, pp. 697-719.
- P. Dolog et al. (2007). Specification, Authoring and Prototyping of Personalized Workplace Learning Solutions. *International Journal of Learning Technology*, Vol. 3, No. 3, pp 286-308.
- R. Dunn, S. Griggs (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*. New York: St John's University.
- E. A. Edmonds (1981). Adaptive Man-Computer Interfaces. *Computing skills in the user interface*, Computer and People series, New York, Academic Press.
- N.J. Entwistle (1998). Improving Teaching through Research on Student Learning. In J.J.F. Forrest (ed.): *University teaching: international perspectives*, New York: Garland.
- R. M. Felder, L. K. Silverman (1988). Learning and Teaching Styles in Engineering Education, *Engineering Education*, 78 (7). Preceded by a preface in 2002: <http://www4.ncsu.edu/unity/lockers/users/f/felder/public/Papers/LS-1988.pdf>
- R. M. Felder (1993). Reaching the Second Tier: Learning and Teaching Styles in College Science Education. *College Science Teaching*, 23 (5), pp. 286-290.
- N. D. Flemming (1995). I am Different; Not Dumb. Modes of Presentation (V.A.R.K.) in the Tertiary Classroom. In A. Zelmer (ed.): *Research and development in higher education. Proceedings of the 1995 annual conference of the higher education and research development society of Australia (HERDSA)*, Vol. 18, pp. 308–313.
- C. Frasson, T. Mengelle, E. Aïmeur, G. Gouardères (1996). An Actor-based Architecture for Intelligent Tutoring Systems. *Proc. Third International Conference on Intelligent Tutoring Systems, ITS-96*, Berlin: Springer Verlag, pp. 57-65.
- P. Garcia, A. Amandi, S. Schiaffino, M. Campo (2007). Evaluating Bayesian Networks' Precision for Detecting Students' Learning Styles. *Computers & Education*, 49 (3), pp. 794-808.
- H. Gardner (1991). *The Unschooled Mind: How Children Think and How Schools Should Teach*. Basic Books Inc.
- H. Gardner (1993). *Multiple Intelligences: The Theory in Practice*. Basic Books, New York.
- J. Gascuena, A. Fernandez-Caballero, P. Gonzalez (2006). Domain Ontology for Personalized E-Learning in Educational Systems. *Proc. 6th IEEE Intl. Conf. on Advanced Learning Technologies - ICALT 2006*, IEEE Computer Society Press.

- G. Geser (2007). *OLCOS Roadmap 2012 - Open Educational Practices and Resources*, Austria.
- J.E. Gilbert, C.Y. Han (1999). Adapting Instruction in Search of 'A Significant Difference', *Journal of Network and Computer Applications*, 22.
- D. Gordon, G. Bull (2004). The Nexus Explored: A Generalised Model of Learning Styles. *Proc. of Society for Information Technology and Teacher Education International Conference 2004*, pp. 917-925.
- S. Graf, R. Bekele (2006). Forming Heterogeneous Groups for Intelligent Collaborative Learning Systems with Ant Colony Optimization. *Proc. International Conference on Intelligent Tutoring Systems (ITS 06)*, Jhongli, Taiwan, pp. 217-226.
- S. Graf (2007). *Adaptivity in Learning Management Systems Focussing on Learning Styles*, PhD Thesis, Vienna University of Technology, Austria.
- S. Graf, Kinshuk (2008). Analysing the Behaviour of Students in Learning Management Systems with respect to Learning Styles. *Studies in Computational Intelligence*, Vol. 93, Springer, pp. 53-74.
- M. Graff (2003). Assessing Learning from Hypertext: An Individual Differences Perspective. *Journal of Interactive Learning Research*, 14 (4), pp. 425-438.
- A. F. Grasha (1984). Learning Styles: the Journey from Greenwich Observatory (1796) to the College Classroom (1984). *Improving College and University Teaching*, 32(1), pp. 46-53.
- A. F. Grasha (1995). *Practical Applications of Psychology*. New York : HarperCollins.
- J. Greer, G. McCalla, J. Cooke, J. Collins, V. Kumar, A. Bishop, J. Vassileva (1998). The Intelligent Help Desk: Supporting Peer-Help in a University Course. *Proc. Int. Conf. on Intelligent Tutoring Systems – ITS'98*, Springer-Verlag, pp. 494–503.
- A.F. Gregorc (1979). Learning/Teaching Styles: Potent Forces behind Them. *Educational Leadership*, 36 (4).
- A. F. Gregorc (1984). Style as a Symptom: a Phenomenological Perspective. *Theory into Practice*, 23(1), pp. 51-55.
- A.F. Gregorc (1985). *Style Delineator: A Self-Assessment Instrument for Adults*. Columbia: Gregorc Associates Inc.
- T. Heift, D. Nicholson (2001). Web Delivery of Adaptive and Interactive Language Tutoring. *International Journal of Artificial Intelligence in Education*, 12(4), pp. 310-324.
- N. Henze, W. Nejdil (1998). *Student Modeling in an Active Learning Environment Using Bayesian Networks*. Technical report, University of Hannover, Germany.

- N. Henze, W. Nejdl (1999). *Bayesian Modeling for Adaptive Hypermedia Systems*. Technical report, University of Hannover, Germany.
- N. Henze, W. Nejdl (2001). Adaptation in Open Corpus Hypermedia. *International Journal of Artificial Intelligence in Education*, 12(4), pp. 325-350.
- N. Henze, P. Dolog, W. Nejdl (2004) Reasoning and Ontologies for Personalized E-Learning in the Semantic Web. *Educational Technology & Society*, 7 (4), pp. 82-97.
- N. Herrmann (1996). *The Whole Brain Business Book*. McGraw-Hill.
- P. Honey, A. Mumford (2000). *The Learning Styles Helper's Guide*. Maidenhead: Peter Honey Publications Ltd.
- G. J. Houben, L. Aroyo, P. De Bra, D. Dicheva (2005). Adaptation Engineering in Adaptive Concept-Based Systems. In S. Y. Chen, G. D. Magoulas (eds.): *Adaptable and Adaptive Hypermedia Systems*, IRM Press.
- A. Inaba, T. Supnithi, M. Ikeda, R. Mizoguchi, J. Toyoda (2000). How Can We Form Effective Collaborative Learning Groups? *Proc. Int. Conf. on Intelligent Tutoring Systems*, Springer-Verlag, pp. 282–291.
- T. Isakowitz, M. Bieber, F. Vitali (1998). Web Information Systems. *Communications of the ACM*, 41(1), pp. 78-80.
- C. Jackson (2002). *Manual of the Learning Styles Profiler*.
- I. Jacobson, G. Booch, J. Rumbaugh (1999). *The Unified Software Development Process*. Boston: Addison Wesley.
- W. James, D. Gardner (1995). Learning Styles: Implications for Distance Learning. *New Directions for Adult and Continuing Education*, 67.
- D. H. Jonassen, B. L. Grabowski (1993). *Handbook of Individual Differences: Learning and Instruction*, Hove: LEA.
- J. Jovanovic, D. Gasevic, V. Devedzic (2006). Dynamic Assembly of Personalized Learning Content on the Semantic Web. *Proc. 3rd European Semantic Web Conference*, Budva, Montenegro, pp. 544-558.
- C. Karagiannidis, D. Sampson (2004). Adaptation Rules Relating Learning Styles Research and Learning Objects Metadata. *Proc. Workshop on Individual Differences in Adaptive Hypermedia*, The University of Technology, Netherlands, August 23–26, 2004.
- J. Kay (2001). Learner Control. *User Modeling and User-Adapted Interaction*, 11, pp. 111-127.
- J. Keefe (1979). Learning Style: An Overview. *NASSP's Student Learning Styles: Diagnosing and Prescribing Programs*, pp. 1–17.

- J. Keefe, B. Ferrell (1990). Developing a Defensible Learning Style Paradigm, *Educational Leadership*, 48 (2).
- D. Kelly, B. Tangney (2006). Adapting to Intelligence Profile in an Adaptive Educational System. *Interacting with Computers*, 18, pp. 385–409.
- B. Klicek, M. Zekic-Susac (2003). Toward Integrated and Revised Learning Styles Theory Supported by Web and Multimedia Technologies. *Proc. 8th Annual Conference of the European Learning Styles Information Network*.
- A. Knapp, N. Koch, F. Moser, G. Zhang (2003). ArgoUWE: A Case Tool for Web Applications. *Proc. First Intl. Workshop on Engineering Methods to Support Information Systems Evolution*.
- A. Kobsa (2001). Generic User Modeling Systems. *User Modeling and User-Adapted Interaction*, Springer Netherlands, vol. 11, no. 1-2, pp. 49-63.
- N. Koch (2001). *Software Engineering for Adaptive Hypermedia Applications*. PhD Thesis.
- N. Koch, M. Wirsing (2002). The Munich Reference Model for Adaptive Hypermedia Applications. *Proc. 2nd Intl. Conference on Adaptive Hypermedia and Adaptive Web-based Systems*, pp. 213-222.
- E. B. Koffman, J. M. Perry (1976). A Model for Generative CAI and Concept Selection. *International Journal on the Man-Machine Studies*, 8, pp. 397-410.
- D.A. Kolb (1999). *The Kolb Learning Style Inventory*, Version 3, Hay Group, Boston.
- D. A. Kolb (2000). *Facilitator's guide to learning*. Boston: Hay/McBer.
- M. Kravcik (2004). Specification of Adaptation Strategy by FOSP Method. *AH 2004: Workshop Proceedings*, TU/e, pp. 429-435.
- M. Kravcik, M. Specht (2004). Authoring Adaptive Courses - ALE Approach. *Advanced Technology for Learning*, 1(4), pp. 215-220.
- M. Kravcik, D. Gasevic (2007). Leveraging the Semantic Web for Adaptive Education. *Journal of Interactive Media in Education* (Adaptation and IMS Learning Design. Special Issue, ed. Daniel Burgos).
- H. A. Landsberger (1958). *Hawthorne Revisited: Management and the Worker, Its Critics, and Developments in Human Relations in Industry*, N.Y.S. School of Industrial and Labor Relations, Cornell University, Ithaca, New York.
- C. H. M. Lee, Y. W. Cheng, S. Rai, A. Depickere (2005). What Affect Student Cognitive Style in the Development of Hypermedia Learning System? *Computers & Education*, 45, pp. 1–19.

- Y. Levy (2006). *Assessing the Value of E-Learning Systems*. Information Science Publishing.
- A. Lippman (1980). Movie-Maps: An Application of the Optical Videodisc to Computer Graphics. *Proc. 7th annual conference on Computer graphics and interactive techniques*, Seattle, Washington, United States, pp. 32–42.
- G. I. McCalla, J. E. Greer, V. S. Kumar, P. Meagher, J. A. Collins, R. Tkatch, B. Parkinson (1997). A Peer Help System for Workplace Training. *Proc. AI-ED'97, 8th World Conference on Artificial Intelligence in Education*. Amsterdam: IOS, pp. 183-190.
- E. Melis, E. Andrès, J. Büdenbender, A. Frishauf, G. Gogvadse, P. Libbrecht, M. Pollet, C. Ullrich (2001). ActiveMath: A Web-based Learning Environment. *International Journal of Artificial Intelligence in Education*, 12(4), pp. 385-407.
- A. Merceron, K. Yacef (2003). A Web-based Tutoring Tool with Mining Facilities to Improve Learning and Teaching. *Proc. AI-Ed'2003*. Amsterdam: IOS Press, pp. 201-208.
- D.P. Mitchell (1994). Learning Style: A Critical Analysis of the Concept and Its Assessment. In R Hoey (ed.): *Design for learning: aspects of educational technology*. London: Kogan Page
- T. Mitchell, S. Y. Chen, R. Macredie (2004). Adapting Hypermedia to Cognitive Styles: Is It Necessary? *Proc. Workshop on Individual Differences in Adaptive Hypermedia*, The University of Technology, Netherlands, August 23–26.
- A. Mitrovic (2003). An Intelligent SQL Tutor on the Web. *International Journal of Artificial Intelligence in Education*, 13(2-4), pp. 171-195.
- H. Mitsuhashi, Y. Ochi, K. Kanenishi, Y. Yano (2002). An Adaptive Web-based Learning System with a Free-Hyperlink Environment. *Proc. Workshop on Adaptive Systems for Web-Based Education, AH'2002*, pp. 81-91.
- G. R. Morrison, S. M. Ross, J. E. Kemp (2001). *Designing Effective Instruction*. John Wiley & Sons.
- M. E. Muller (2005). Learning Adaptive Behaviour. *Adaptable and Adaptive Hypermedia Systems*, IRM Press.
- T. Murray (2003). MetaLinks: Authoring and Affordances for Conceptual and Narrative Flow in Adaptive Hyperbooks. *International Journal of Artificial Intelligence in Education*, 13(2-4), pp. 197-231.
- I.B. Myers, M.H. McCaulley (1985). *Manual: A Guide to the Development and Use of the Myers-Briggs Type Indicator*. Palo Alto, CA: Consulting Psychologists Press.
- T. H. Nelson (1965). A File Structure for the Complex, the Changing and the Indeterminate, *Proc. ACM 20th National Conference*, pp. 84-100.

- T. Oda, H. Satoh, S. Watanabe (1998). Searching Deadlocked Web Learners by Measuring Similarity of Learning Activities. *Proc. Workshop "WWW-Based Tutoring" at 4th International Conference on Intelligent Tutoring Systems (ITS'98)*, August 16-19, 1998. San Antonio, TX.
- T. O'Reilly (2005). What Is Web 2.0. Design Patterns and Business Models for the Next Generation of Software.
<http://www.oreillynet.com/pub/a/oreilly/tim/news/2005/09/30/what-is-web-20.html>
- K. A. Papanikolaou, M. Grigoriadou, H. Kornilakis, G.D. Magoulas (2003). Personalizing the Interaction in a Web-based Educational Hypermedia System: The Case of INSPIRE. *UMUAI*, 13, pp 213-267.
- K. A. Papanikolaou, M. Grigoriadou (2004). Accommodating Learning Style Characteristics in Adaptive Educational Hypermedia Systems. *Proc. Workshop on Individual Differences in Adaptive Hypermedia*, The University of Technology, Netherlands, August 23–26, 2004.
- K. A. Papanikolaou, A. Mabbott, S. Bull, M. Grigoriadou (2006). Designing Learner-Controlled Educational Interactions Based on Learning/Cognitive Style and Learner Behaviour. *Interacting with Computers*, 18, pp. 356–384.
- A. Paramythis, S. Weibelzahl (2005). A Decomposition Model for the Layered Evaluation of Interactive Adaptive Systems. *Proc. 10th International Conference on User Modeling (UM2005)*, LNAI 3538, Springer Verlag, pp. 438-442.
- P. Paredes, P. Rodriguez (2004). A Mixed Approach to Modelling Learning Styles in Adaptive Educational Hypermedia. *Advanced Technology for Learning*, 1 (4), pp. 210–215.
- G. Pask (1988). Learning Strategies, Teaching Strategies, and Conceptual or Learning Style. *Learning strategies and learning styles*. New York, Plenum Press: 83-100.
- M.P. Paule Ruiz, J.R Pérez, M. González (2003). Feijoo.net. An Approach to Personalized e-Learning Using Learning Styles. *Proc. ICWE*, pp. 112–115.
- M. P. Paule Ruiz, M. J. Fernández Díaz, F. Ortín Soler, J. R. Pérez Pérez (2008). Adaptation in Current E-Learning Systems, *Computer Standards & Interfaces*, Elsevier, vol. 30, issue 1-2, pp 62-70.
- N.E. Perry, L. Phillips, L. R. Hutchinson (2006). Preparing Student Teachers to Support for Self-Regulated Learning. *Elementary School Journal*, 106, pp. 237-254.
- D. Poole, A. Mackworth, R. Goebel (1998). *Computational Intelligence: A Logical Approach*, Oxford University Press.
- E. Popescu (2006). Adaptive Educational Hypermedia Systems. Internal research report, University of Craiova, Romania, 31 October 2006.

- E. Popescu, P. Trigano, C. Badica (2006). eDalgo: Designing Personalized Courseware for Teaching Introductory Programming. *Proc. EAEEIE 17*, pp. 290-295.
- E. Popescu (2007a). Adaptive Educational Hypermedia Systems: Student Modeling with Respect to Learning Styles. Poster presented at EIAH 2007 (thematic school on learning environments), 7-12 July 2007, Saint Quentin sur Isère, France.
- E. Popescu (2007b). User Modeling: Methods and Techniques Specific for E-learning. Internal research report, University of Craiova, Romania, 29 June 2007.
- E. Popescu (2007c). Adaptive Technologies in Intelligent Web-based Educational Systems. Internal research report, University of Craiova, Romania, 6 November 2007.
- E. Popescu, P. Trigano, C. Badica (2007a). Towards a Unified Learning Style Model in Adaptive Educational Systems. *Proc. ICALT 2007*, IEEE Computer Society Press, pp. 804-808.
- E. Popescu, P. Trigano, C. Badica (2007b). Adaptive Educational Hypermedia Systems: A Focus on Learning Styles. *Proc. EUROCON 2007*, IEEE Press, pp. 2473-2478.
- E. Popescu, C. Badica, P. Trigano (2007c). Rules for Learner Modeling and Adaptation Provisioning in an Educational Hypermedia System. *Proc. SYNASC 2007 (workshop RuleApps)*, IEEE Computer Society Press, pp. 492-499.
- E. Popescu, P. Trigano, C. Badica (2007d). Evaluation of a Learning Management System for Adaptivity Purposes. *Proc. ICCGI 2007*, IEEE Computer Society Press, pp. 9.1-9.6.
- E. Popescu, P. Trigano, C. Badica (2007e). Approaches to Adaptivity Provisioning in E-learning Systems. *Proc. ITHET 2007 (the 8th International Conference on Information Technology based Higher Education and Training)*, Kumamoto, Japan, 10-13 July 2007, pp. 536-540.
- E. Popescu (2008a). An Artificial Intelligence Course Used to Investigate Students' Learning Style. *Proc. ICWL 2008*, Lecture Notes in Computer Science, Vol. 5145, Springer, pp. 122 – 131.
- E. Popescu (2008b). Une analyse exploratoire des corrélations entre les traces des apprenants et leurs styles d'apprentissage. *Proc. RJC-EIAH*, Lille 15 – 16 May 2008, pp. 119 – 124.
- E. Popescu, C. Badica, P. Trigano (2008a). Learning Objects' Architecture and Indexing in WELSA Adaptive Educational System. *Scalable Computing: Practice and Experience*, Vol. 9(1), pp. 11-20.
- E. Popescu, C. Badica, P. Trigano (2008b). Analyzing Learners' Interaction with an Educational Hypermedia System: a Focus on Learning Styles. *Proc. SAINT2008 (workshop SPeL)*, IEEE Computer Society Press, pp. 321-324.

- E. Popescu, P. Trigano, C. Badica (2008c). Relations between Learning Style and Learner Behavior in an Educational Hypermedia System: An Exploratory Study. *Proc. ICALT 2008*, IEEE Computer Society Press, pp. 725-726.
- E. Popescu, P. Trigano, C. Badica (2008d). Intégrer les styles d'apprentissage dans les EIAHs, *Proc. CIFA 2008*.
- E. Popescu, P. Trigano, C. Badica, B. Butoi, M. Duica (2008e). A Course Authoring Tool for WELSA Adaptive Educational System. *Proc. ICC 2008*, pp. 531-534.
- E. Popescu, C. Badica, P. Trigano (2008f). Description and Organization of Instructional Resources in an Adaptive Educational System Focused on Learning Styles. *Advances in Intelligent and Distributed Computing, Studies in Computational Intelligence Series*, Vol. 78, Springer, pp. 177-186.
- E. Popescu, P. Trigano, M. Preda (2008g). Data Requirements for Detecting Student Learning Style in an Educational Hypermedia System. *Proc. European Computing Conference - Volume 2, Series: Lecture Notes in Electrical Engineering*, Vol. 28, Springer.
- C. M. Reigeluth (1999). The Elaboration Theory: Guidance for Scope and Sequence Decisions. In Reigeluth C.M. (ed.): *Instructional-Design Theories and Models*, Volume II, Lawrence Erlbaum Associates, pp. 425-453.
- M. Reynolds (1997). Learning Styles: a Critique. *Management Learning*, 28(2), pp. 115-133.
- R. J. Riding (1991). *Cognitive Styles Analysis*, Birmingham. Learning and Training Technology.
- R. J. Riding, S. Rayner (1998). *Cognitive Styles and Learning Strategies: Understanding Style Differences in Learning and Behaviour*, David Fulton Publishers.
- H. Rittel, M. Webber (1973). *Dilemmas in a General Theory of Planning*. Amsterdam, Elsevier Scientific Publishing Company, Inc.
- M. J. Roberts, E. J. Newton (2001). Understanding Strategy Selection. *Intl. Journal of Computer Studies*, 54, pp. 137-154.
- C. Romero, S. Ventura, P.D. Bra, C. Castro (2003). Discovering Prediction Rules in AHA! Courses. *Proc. 9th International User Modeling Conference*, Berlin: Springer Verlag, Vol. 2702, pp. 25-34.
- A. P. Rovai, K.T. Barnum (2003). On-Line Course Effectiveness: An Analysis of Student Interactions and Perceptions of Learning. *Journal of Distance Education*, 18 (1), pp. 57-73.
- E. Sadler-Smith (2001). The Relationship between Learning Style and Cognitive Style. *Personality and Individual Differences*, 30, pp. 609-616.

- D. Sampson, C. Karagiannidis, F. Cardinali (2002). An Architecture for Web-Based e-Learning Promoting Re-usable Adaptive Educational e-Content. *Educational Technology & Society Journal*, 5(4).
- E. Sangineto, N. Capuano, M. Gaeta, A. Micarelli (2007). Adaptive Course Generation through Learning Styles Representation. *Journal of Universal Access in the Information Society*, DOI 10.1007/s10209-007-0101-0, Springer.
- D. H. Schunk, B. J. Zimmerman (1998). *Self-Regulated Learning: From Teaching to Self-Reflective Practice*. New York: Guilford.
- D. Schwabe, G. Rossi (1998). Developing Hypermedia Applications Using OOADM. *Proc. Workshop on Hypermedia Development Process, Methods and Models*.
- B. Shearer (1996). *The MIDAS Handbook of Multiple Intelligences in the Classroom*. Greyden Press, Ohio.
- H. Shi, O. Rodriguez, S. Chen, Y. Shang (2004). Open Learning Objects as an Intelligent Way of Organizing Educational Material. *International Journal on E-Learning*, 3(2), pp. 51–63.
- M. Sigala (2008). Integrating Web 2.0 in E-Learning Environments: A Socio-Technical Approach. *International Journal of Knowledge and Learning*, Vol. 3, No. 6, pp. 628-648.
- G. T. da Silva, M. C. Rosatelli (2006). Adaptation in Educational Hypermedia Based on the Classification of the User Profile. *Proc. Intelligent Tutoring Systems 2006*, LNCS vol. 4053, Springer, pp. 268-277.
- R. Sison, M. Shimura (1998). Student Modeling and Machine Learning. *International Journal of Artificial Intelligence in Education*, 9, pp. 128–158.
- A. S. G. Smith, A. Blandford (2003). MLTutor: An Application of Machine Learning Algorithms for an Adaptive Web-based Information System. *International Journal of Artificial Intelligence in Education*. 13 (2-4), pp. 233-260.
- A. Soller, A. Lesgold (2003). A Computational Approach to Analysing Online Knowledge Sharing Interaction. *Proc. AI-ED'2003*, Amsterdam: IOS Press, pp. 253-260.
- B. Soloman, R. M. Felder (1998). *Index of learning styles questionnaire*. <http://www.engr.ncsu.edu/learningstyles/ilsweb.html>.
- N. Stash, A.I. Cristea, P. De Bra (2005). Explicit Intelligence in Adaptive Hypermedia: Generic Adaptation Languages for Learning Preferences and Styles. *Proc. 16th ACM Conference on Hypertext and Hypermedia (International Workshop on Combining Intelligent and Adaptive Hypermedia Methods/Techniques in Web-Based Education Systems)*, September, Salzburg, Austria.
- N. Stash (2007). *Incorporating Cognitive/Learning Styles in a General-Purpose Adaptive Hypermedia System*. PhD Thesis, Eindhoven University of Technology, Netherlands.

- R. Stathacopoulou, M. Grigoriadou, M. Samarakou, D. Mitropoulos (2007). Monitoring Students' Actions and Using Teachers' Expertise in Implementing and Evaluating the Neural Network-based Fuzzy Diagnostic Model. *Expert Systems with Applications*, Elsevier, 32, pp. 955–975.
- K. Steffens (2006). Self-Regulated Learning in Technology Enhanced Learning Environments: Lessons of a European Peer Review. *European Journal of Education*, vol. 41, no. 3-4, pp. 353-379.
- R.J. Sternberg (1999). *Thinking Styles*. Cambridge: Cambridge University Press.
- B. Towle, M. Halm (2005). Designing Adaptive Learning Environments with Learning Design. In R. Koper and C. Tattersall (eds.): *Learning Design. A Handbook on Modelling and Delivering Networked Education and Training*. The Netherlands: Springer, pp. 215-226.
- E. Triantafyllou, A. Pomportsis, S. Demetriadis (2003). The Design and the Formative Evaluation of an Adaptive Educational System Based on Cognitive Styles. *Computers & Education*, 41, pp. 87-103.
- C. Ullrich (2005). The Learning-Resource-Type is Dead, Long Live the Learning-Resource-Type!. *Learning Objects and Learning Designs*, 1, pp. 7–15.
- J.D. Vermunt (1998). The Regulation of Constructive Learning Processes. *British Journal of Educational Psychology*, 68, pp. 149–171.
- R. Vdovjak, F. Fransicar, G.J. Houben, P. Barna (2003). Engineering Semantic Web Information Systems in Hera. *Journal of Web Engineering*, 2 (1/2), pp. 3-26.
- T. Wang, K. Wang, Y. Huang (2008). Using a Style-based Ant Colony System for Adaptive Learning. *Expert Systems with Applications*, 34, 4, pp. 2449-2464.
- G. Weber, P. Brusilovsky (2001). ELM-ART: An Adaptive Versatile System for Web-Based Instruction. *International Journal of Artificial Intelligence in Education*.
- S. Weibelzahl (2005). Problems and Pitfalls in the Evaluation of Adaptive Systems. In S. Y. Chen, G. D. Magoulas (eds.): *Adaptable and Adaptive Hypermedia Systems*, IRM Press.
- D. Wen, S. Graf, C. H. Lan, T. Anderson, Kinshuk, K. Dickson (2007). Adaptive Assessment in Web-based learning. *Proc. IEEE International Conference on Multimedia and Expo (ICME 2007)*, pp. 1846-1849.
- A. Wexelblat, P. Mayes (1997). Footprints: History Rich Web Browsing. *Proc. Conference on Computer-Assisted Information Retrieval*, pp. 75-84.
- C. Wolf (2002). iWeaver: Towards an Interactive Web-Based Adaptive Learning Environment to Address Individual Learning Styles. *Proc. ICL 2002*.

- H. A. Witkin (1962). *Psychological Differentiation: Studies of Development*. New York: Wiley.
- H. Wu, E. De Kort, P. De Bra (2001). Design Issues for General-Purpose Adaptive Hypermedia Systems. *Proc. ACM Conference on Hypertext and Hypermedia (Hypertext'01)*, pp. 141-150.
- M. Yudelso, T. Gavrilova, P. Brusilovsky (2005). Towards User Modeling Meta-ontology. *Proc. International User Modeling Conference*, Berlin: Springer Verlag, pp. 448-452.
- B. J. Zimmerman, D. H. Schunk (1989). *Self-Regulated Learning and Academic Achievement: Theory, Research, and Practice*. New York: Springer.

Web references

- ADAPTIT (2003). *D9.2. Final report*. Project deliverable report, available online at <http://www.adaptit.org>.
- ADL SCORM (2008). <http://www.adlnet.gov/scorm/index.aspx>.
- Ajax (2008). Asynchronous JavaScript and XML.
<http://java.sun.com/developer/technicalArticles/J2EE/AJAX>
- ALFANET (2002). *D1.2. State-of-the-art*. Project deliverable report, available online at: <http://rtd.softwareag.es/alfanet>.
- ALFANET (2005). *D8.2 Public final report*. Project deliverable report, available online at: <http://rtd.softwareag.es/alfanet>.
- ATutor (2008). <http://www.atutor.ca>.
- Blackboard (2008). <http://www.blackboard.com>.
- DCMI (2008). Dublin Core Metadata Initiative. <http://dublincore.org>.
- dotLRN (2008). <http://dotlrn.org>
- IEEE LOM (2008). <http://ltsc.ieee.org/wg1>.
- IMS Global Learning Consortium (2008). <http://imsglobal.org>.
- IMS MD (2008). <http://www.imsglobal.org/metadata/index.html>.
- JSP (2008). JavaServer Pages Technology. <http://java.sun.com/products/jsp>.
- Moodle (2008). <http://moodle.org>

References

MySQL (2008). <http://www.mysql.com>.

Oxygen (2008). Oxygen XML Editor. <http://www.oxygenxml.com>.

SPSS (2008). SPSS 16.0 for Windows. <http://www.spss.com>.

TELEPEERS (2008). <http://www.hds.utc.fr/telepeers>.

Tomcat (2008). Apache Tomcat. <http://tomcat.apache.org>.

XML DOM (2008). <http://www.w3.org/DOM>

Abstract

The ultimate goal of adaptive educational hypermedia systems (AEHS) is to provide a learning experience that is individualized to the particular needs of the learners, from the point of view of knowledge level, goals, motivation, individual differences etc. The focus of our thesis is on the learning style as the adaptation criterion, since it is one of the individual differences that play an important role in learning, according to educational psychologists.

The first step towards providing adaptivity is selecting a good taxonomy of learning styles. We advocate the use of a "unified learning style model" (ULSM), which integrates characteristics from several models proposed in the literature, thus establishing a unified core vocabulary.

The traditional method for diagnosing learning style implies having the students fill in a dedicated psychological questionnaire. What we propose in this thesis is an implicit modeling method, which is based on the analysis and interpretation of student behavior in the system, not requiring any additional effort from the part of the students and bypassing the reliability and validity problems of the existing learning style questionnaires. The approach was validated through experimental research, obtaining good precision results.

The next step of our research was to identify the adaptation technologies that best serve learners with different learning styles and define the corresponding adaptation rules. The effectiveness was confirmed by means of an experimental study: the results obtained (student behavior, performance, efficiency and satisfaction) proved the positive effect that our adaptation to learning styles has on the learning process.

Based on the methods and techniques proposed for modeling and adaptation, we designed and implemented a dedicated e-learning platform, called WELSA (**Web-based Educational system with Learning Style Adaptation**), which includes several functionalities: i) a course player for the students, enhanced with learner tracking capabilities and an adaptation component; ii) an analysis tool, used for identifying students' learning preferences; iii) a course editor for the teachers, to help them author courses in the required format. The final step of our research was the global evaluation of WELSA system. The analysis of students' answers to the survey instruments revealed the high degree of learner satisfaction with the system, as well as their desire to use WELSA system on an everyday basis.

The subject required an interdisciplinary approach, demanding the synergy of computer science and instructional sciences (adaptive hypermedia, learning management systems, user modeling, educational psychology). The findings and results obtained in this thesis open up many research perspectives for the AEHS field in general and the learning style based adaptive educational systems in particular.

Keywords: e-learning, learner modeling, learning style, adaptive educational hypermedia

Résumé

Un des objectifs principaux de la recherche actuelle dans le domaine des EIAH est de fournir une expérience éducative personnalisée, qui correspond aux besoins spécifiques de chaque apprenant (niveau de connaissances, buts, motivation etc.). Cette thèse traite de style d'apprentissage en tant que critère d'adaptation, étant donné que les différences individuelles jouent un rôle important dans le processus d'apprentissage.

Une première étape consiste à choisir une taxonomie appropriée pour les styles d'apprentissage. Nous proposons un « modèle unifié de style d'apprentissage », qui englobe des caractéristiques de plusieurs modèles traditionnels, établissant un vocabulaire de base unifié.

La méthode traditionnelle pour l'identification des styles d'apprentissage consiste à appliquer des questionnaires dédiés. Nous proposons dans cette thèse une méthode de modélisation implicite, basée sur l'analyse et l'interprétation du comportement de l'apprenant dans le système, qui ne nécessite pas un effort supplémentaire de la part de l'étudiant et qui élimine les problèmes de fidélité et de validité des questionnaires actuels. L'approche a été validée expérimentalement, obtenant des valeurs de précision élevées.

L'étape suivante a été d'identifier les technologies d'adaptation qui servent le mieux chaque style d'apprentissage et de définir les règles d'adaptation correspondantes. L'efficacité a été confirmée par le biais d'une étude expérimentale: les résultats obtenus (indicateurs de comportement de l'étudiant, performance, efficacité, degré de satisfaction) montrent l'influence positive de notre adaptation sur le processus d'apprentissage.

A partir des méthodes et techniques proposées pour la modélisation et l'adaptation, nous avons conçu un système hypermédia éducatif nommé WELSA (**Web-based Educational system with Learning Style Adaptation**), qui offre les fonctionnalités suivantes: i) une plateforme d'apprentissage pour les étudiants, qui leur permet de visualiser les cours, enrichie avec une fonctionnalité de collecte de traces et un module d'adaptation; ii) un outil d'analyse des traces pour l'identification des styles d'apprentissage; iii) un outil auteur pour les enseignants, qui leur permet de créer des cours conformes au format interne WELSA. La dernière partie de notre recherche a été l'évaluation globale de la plateforme WELSA. L'analyse des réponses des étudiants aux questionnaires a révélé le haut degré de satisfaction des étudiants avec le système, ainsi que leur désir d'utiliser WELSA au quotidien.

Le sujet nécessite une approche interdisciplinaire, exigeant la synergie entre les technologies de l'information et de la communication et les sciences de l'éducation (systèmes hypermédiatifs adaptatifs, plateformes d'apprentissage en ligne, modélisation de l'apprenant, psychologie éducative). Les conclusions et résultats obtenus dans cette thèse ouvrent beaucoup de perspectives de recherche pour le domaine des systèmes hypermédiatifs adaptatifs pour le e-learning.

Mot-clefs: EIAH, modélisation de l'apprenant, style d'apprentissage, système hypermédia adaptatif.

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Publications

Papers in peer-reviewed scientific journals

- **Elvira Popescu**, Costin Badica, Philippe Trigano, *Learning Objects' Architecture and Indexing in WELSA Adaptive Educational System*, Scalable Computing: Practice and Experience, Vol. 9(1), ISSN 1895-1767, pp. 11-20, 2008.
- Costin Badica, Amelia Badica, **Elvira Popescu**, Ajith Abraham, *L-Wrappers: Concepts, Properties and Construction: A Declarative Approach to Data Extraction from Web Sources*, Soft Computing - A Fusion of Foundations, Methodologies and Applications, Vol. 11, No. 8/June, Springer Berlin / Heidelberg, ISSN: 1433-7479, pp. 753-772, 2007.
- **Elvira Popescu**, Amelia Badica, Costin Badica, *Mining Travel Resources on the Web Using L-Wrappers*, Lecture Notes in Artificial Intelligence, Vol. 4029, Springer, ISSN: 0302-9743, pp. 1199-1208, 2006.
- Philippe Trigano, **Elvira Popescu**, Ecaterina Giacomini, *Creating and Implementing Project-Based E-Learning Scenarios*, Annals of the University of Craiova, Automation, Computers, Electronics and Mechatronics Series, Vol. 3 (30), No. 2, Universitaria Press, Craiova, Romania, ISSN: 1841-0626, pp. 195-204, 2006.
- Costin Badica, Amelia Badica, **Elvira Popescu**, *Tuples Extraction from HTML Using Logic Wrappers and Inductive Logic Programming*, Advances in Web Intelligence, Lecture Notes in Artificial Intelligence, vol. 3528, Springer-Verlag, ISSN: 0302-9743, pp.44-50, 2005.
- **Elvira Popescu**, *Modelling Units of Learning: A Practical Exploration of IMS Learning Design*, ELSE Software Journal, no. 24/XII, Sitech Press, Craiova, Romania, ISSN: 1221-4469, pp. 24-33, 2005.
- Razvan Tanasie, **Elvira Popescu**, Daniel Nistor, *An approach to formal specification by concrete examples*, ELSE Software Journal, no. 25/XII, Sitech Press, Craiova, Romania, ISSN: 1221-4469, pp. 107-127, 2005.

Book chapters

- Costin Badica, Amelia Badica, **Elvira Popescu**, *Using Logic Programming and XML Technologies for Data Extraction from Web Pages*, Dariusz Król and Ngoc Thanh Nguyen (Eds.): Intelligence Integration in Distributed Knowledge Management, Information Science Reference, ISBN: 978-1-59904-576-4, 2008.

Papers in conference proceedings

- **Elvira Popescu**, *An Artificial Intelligence Course Used to Investigate Students' Learning Style*, Proceedings ICWL 2008, Lecture Notes in Computer Science, Vol. 5145, pp. 122-131, Springer, ISBN 978-3-540-85032-8, 2008.
- **Elvira Popescu**, Costin Badica, Philippe Trigano, *Analyzing Learners' Interaction with an Educational Hypermedia System: a Focus on Learning Styles*, Proceedings

- SAINT2008 (workshop SPeL), pp. 321-324, IEEE Computer Society Press, ISBN: 978-0-7695-3297-4, 2008.
- **Elvira Popescu**, Philippe Trigano, Costin Badica, *Relations between Learning Style and Learner Behavior in an Educational Hypermedia System: An Exploratory Study*, Proceedings ICALT 2008, pp. 725-726, IEEE Computer Society Press, ISBN: 978-0-7695-3167-0, 2008.
 - **Elvira Popescu**, *Une analyse exploratoire des corrélations entre les traces des apprenants et leurs styles d'apprentissage*, Proceedings RJC-EIAH, Lille, France, 15 – 16 May 2008, pp. 119-124, 2008.
 - **Elvira Popescu**, Philippe Trigano, Costin Badica, *Intégrer les styles d'apprentissage dans les EIAHs*, Proceedings CIFA 2008, ISBN: 978-2-915913-24-8, 2008.
 - **Elvira Popescu**, Philippe Trigano, Costin Badica, Bogdan Butoi, Marius Duica, *A Course Authoring Tool for WELSA Adaptive Educational System*, Proceedings ICC 2008, pp. 531-534, ISBN: 978-973-746-897-0, 2008.
 - Costin Badica, **Elvira Popescu**, Grzegorz Frackowiak, Maria Ganzha, Marcin Paprzycki, Michal Szymczak, Myon-Woong Park, *On Human Resource Adaptability in an Agent-Based Virtual Organization*, New Challenges in Applied Intelligence Technologies, Studies in Computational Intelligence Series, Vol. 134, pp. 111-120, Springer, ISBN: 978-3-540-79354-0, 2008.
 - **Elvira Popescu**, Costin Badica, Philippe Trigano, *Description and Organization of Instructional Resources in an Adaptive Educational System Focused on Learning Styles*, Advances in Intelligent and Distributed Computing, Studies in Computational Intelligence Series, Vol. 78, pp. 177-186, Springer, ISBN: 978-3-540-74929-5, 2008.
 - Adriana Dobriceanu, Laurentiu Biscu, Costin Badica, **Elvira Popescu**, *Considerations on the Design and Implementation of an Agent-Based Auction Service*, Advances in Intelligent and Distributed Computing, Studies in Computational Intelligence Series, Vol. 78, pp. 75-84, Springer, ISBN: 978-3-540-74929-5, 2008.
 - **Elvira Popescu**, Philippe Trigano, Mircea Preda, *Data Requirements for Detecting Student Learning Style in an Educational Hypermedia System*, Proceedings of the European Computing Conference - Volume 2, Series: Lecture Notes in Electrical Engineering, Vol. 28, Springer, ISBN: 978-0-387-84818-1, 2009.
 - **Elvira Popescu**, Philippe Trigano, Costin Badica, *Towards a Unified Learning Style Model in Adaptive Educational Systems*, Proceedings ICALT 2007, pp. 804-808, IEEE Computer Society Press, ISBN: 978-0-7695-2916-5, 2007.
 - **Elvira Popescu**, Philippe Trigano, Costin Badica, *Adaptive Educational Hypermedia Systems: A Focus on Learning Styles*, Proceedings EUROCON 2007, pp. 2473-2478, IEEE Press, ISBN: 1-4244-0813-X, 2007.
 - **Elvira Popescu**, Costin Badica, Philippe Trigano, *Rules for Learner Modeling and Adaptation Provisioning in an Educational Hypermedia System*, Proceedings SYNASC 2007 (workshop RuleApps), pp. 492-499, IEEE Computer Society Press, ISBN: 0-7695-3078-8, 2007.
 - M. Ganzha, M. Paprzycki, M. Gawinecki, M. Szymczak, G. Frackowiak, C. Badica, **E. Popescu**, M-W. Park, *Adaptive Information Provisioning in an Agent-Based Virtual Organization – Preliminary Considerations*, Proceedings SYNASC 2007

- (workshop ACSys), pp 235-242, IEEE Computer Society Press, ISBN: 0-7695-3078-8, 2007.
- **Elvira Popescu**, Philippe Trigano, Costin Badica, *Approaches to Adaptivity Provisioning in E-learning Systems*, Proceedings ITHET 2007 (the 8th International Conference on Information Technology based Higher Education and Training), Kumamoto, Japan, 10-13 July 2007, pp. 536-540, 2007.
 - Amelia Badica, Costin Badica, **Elvira Popescu**, *Application of Logic Wrappers to Hierarchical Data Extraction from HTML*, EPIA Workshops 2007 (13th Portuguese Conference on Artificial Intelligence), Lecture Notes in Computer Science, Vol. 4874, pp. 43-52, Springer, ISBN: 978-3-540-77000-8, 2007.
 - Amelia Badica, Costin Badica, **Elvira Popescu**: *Using Logic Wrappers to Extract Hierarchical Data from HTML*, In: K.M. Wegrzyn-Wolska and P.S. Szczepaniak (Eds.): Adv. in Intel. Web, Advances in Soft Computing, Vol. 43, pp. 114–119, Springer, ISBN: 978-3-540-72574-9, 2007.
 - Maria Ganzha, Marcin Paprzycki, **Elvira Popescu**, Costin Badica, Maciej Gawinecki, *Agent-Based Adaptive Learning Provisioning in a Virtual Organization*, Proceedings of the 5th Atlantic Web Intelligence Conference – AWIC'2007, Advances in Soft Computing, Springer, Vol. 43, ISBN: 978-3-540-72574-9, 2007.
 - **Elvira Popescu**, Philippe Trigano, Costin Badica, *Evaluation of a Learning Management System for Adaptivity Purposes*, Proceedings ICCGI 2007, IEEE Computer Society Press, ISBN: 0-7695-2798-1, pp 9.1-9.6, 2007.
 - Elena Doicaru, Ileana Nicolae, **Elvira Popescu**, *E-SSAF – A Powerful E-Learning Tool for State-Space OA-RC and Gm-C Continuous Time Filter Synthesis*, New Horizons in Education and Educational Technology. Proceedings of 6th WSEAS International Conference on Education and Educational Technology, ISBN: 978-960-6766-16-9, pp. 1-6, 2007.
 - **Elvira Popescu**, Philippe Trigano, Costin Badica, *eDalgo: Designing Personalized Courseware for Teaching Introductory Programming*, D. Popescu, O. Bonnaud, M. Hoffmann, J.-M. Thiriet (Eds.): Proceedings EAEEIE 17, Universitaria Press, Craiova, ISBN: 978-973-742-350-4, pp.290-295, 2006.
 - Amelia Badica, Costin Badica, **Elvira Popescu**, *Implementing Logic Wrappers Using XSLT Stylesheets*, P.Dini, C. Poporviciu, C. Dini, G. Van de Velde, E. Borcoci (Eds.): Proceedings ICCGI 2006, IEEE Computer Society Press, ISBN: 0-7695-2629-2, 2006.
 - Costin Badica, Amelia Badica, **Elvira Popescu**, *A New Path Generalization Algorithm for HTML Wrapper Induction*, Proceedings AWIC'06, Studies in Computational Intelligence Series, vol. 23, Springer Berlin / Heidelberg, ISBN: 978-3-540-33879-6, pp. 11-20, 2006.
 - Ecaterina Giacomini Pacurar, Philippe Trigano, **Elvira Popescu**, Paul Crubillé, *Creating Online Courses Models Conforming to IMS Learning Design*, Khaldoun Zreik, Mohammed Ramdani, Mohamed El Adnani, Mostafa Bellafkih (eds) : “Human System Learning. Who is in control ? (Proceedings ICHSL.5/CAPS.5)”, Europia - Publishers, Paris, France, ISBN: 2-909285-33-2, pp. 347-360, 2005.
 - Philippe Trigano, Ecaterina Giacomini, **Elvira Popescu**, *An Approach to Designing Predefined Models of Pedagogical Scenarios for E-learning*, Lungu M., Badica C.

(eds): Proceedings SINTES 12, Universitaria Press, Craiova, Romania, ISBN: 973-742-148-5, pp 668-673, 2005.

- Costin Badica, **Elvira Popescu**, Amelia Badica, *Learning Logic Wrappers for Information Extraction from the Web*, Papazoglou M., Yamazaki, K. (eds.) Proceedings SAINT'2005 (Workshop on Computer Intelligence for Exabyte Scale Data Explosion), IEEE Computer Society Press, ISBN: 0-7695-2263-7, pp.336-339, 2005.

Other papers and talks

- **Elvira Popescu**, *Adaptive Educational Hypermedia Systems: Student Modelling with Respect to Learning Styles*, poster presented at EIAH 2007 (thematic school on learning environments), 7-12 July 2007, Saint Quentin sur Isère, France
- Costin Badica, Amelia Badica, **Elvira Popescu**, *Using Logic Programming and XML Technologies for Data Extraction from Web Pages*, presented at the DoC research seminar, HEUDIASYC Laboratory, University of Technology of Compiègne, France, 20 November 2007.
- **Elvira Popescu**, *User modeling: methods and techniques specific for e-learning*, Internal research report, University of Craiova, Romania, 29 June 2007.
- **Elvira Popescu**, *Adaptive technologies in intelligent web-based educational systems*, Internal research report, University of Craiova, Romania, 6 November 2007.
- A. Benmimoun, A. Ferret, P. Josse, **E. Popescu**, *Rapport Comparatif: Moodle, Dokeos, Claroline, NetUniversité et Scenari*, Technical report, University of Technology of Compiègne, May 2006.
- **Elvira Popescu**, *Sisteme hipermedia dinamice adaptive pentru e-learning*, presented at the Software Engineering Department research seminar, University of Craiova, Romania, 12 December 2006.
- **Elvira Popescu**, *Adaptive educational hypermedia systems for e-learning*, Internal research report, University of Craiova, Romania, 31 October 2006.

Research grants

As grant director

- *Study, design and implementation of an adaptive intelligent web-based system for e-learning*, grant CNCSIS TD, code 167, duration: 2007-2008, financed by the Romanian Ministry of Education and Research – CNCSIS.

As member in the research team

- *eDalgo - eDidactique de l'Algorithmique. Support interactif de cours pour l'apprentissage autonome de l'algorithmique et de la programmation*, interuniversity scientific cooperation program (University of Craiova, University of Technology of Compiègne, France, National Informatics Institute, Algeria, High Commercial

- Studies Institute, Tunisia), ref. 6316PS635, project responsible: Prof. Costin Badica, duration: 2006-2007, financed by AUF (l'Agence Universitaire de la Francophonie).
- *HIPERPROC: Hypermedia techniques for knowledge based representation of organizational processes*, grant CNCSIS 94/2005, grant director: Prof. Costin Badica, duration: 2005-2007, financed by the Romanian Ministry of Education and Research – CNCSIS.
 - *Adaptive web recommender systems based on knowledge represented by logical programs*, grant CNCSIS AT 102/2007, grant director: Lecturer Mircea Preda, duration: 1 year (2007), financed by the Romanian Ministry of Education and Research – CNCSIS.
 - *Stability and oscillations in the dynamic of human-machine systems*, grant IDEI 95/01.10.2007, grant director: Prof. Vladimir Rasvan, duration: 3 years (2007 – 2010), financed by the Romanian Ministry of Education and Research - CNCSIS.
 - *Development of software tools for designing analogue microcircuits*, grant CNCSIS A, code 602, grant director: Conf. Milena Doicaru, duration: 2007 – 2008, financed by the Romanian Ministry of Education and Research – CNCSIS.
 - *System of analysis and computation of polluted electrical network signals and active filter command for harmonics compensation*, grant CEEEX 4049/2006, grant director: Scientific Researcher Eng. Ana Iacob, duration: 2006-2008, financed by the Romanian Ministry of Education and Research.
 - *Pilot – helicopter coupling prevention in critical manoeuvres at the board of ships and marine platforms - ELICOMNAV*, grant CEEEX 449/06.11.2006, scientific responsible for University of Craiova: Prof. Dan Popescu, duration: 2006-2008.
 - *Harmonics filtering-compensation equipment for oil-drilling stations*, grant RELANSIN no. 2122/11.10.2004, contractor: ICMET, partner: University of Craiova, scientific responsible: Prof. Dan Popescu, duration: 2004-2006, financed by the Romanian Ministry of Education and Research.
 - *Nonstandard dynamics in delay systems – Studies and simulated experiments*, grant no. 33062/24.06.2004, theme 10, no. 34677/2005, theme 25, CNCSIS code 318, grant director: Prof. Dan Popescu, duration: 2004-2005, financed by the Romanian Ministry of Education and Research – CNCSIS.

Scholarships

- Research scholarship for young doctoral students (Bd type), financed by CNCSIS (Romanian National University Research Council) (2006 – 2008)
- Research scholarship at HEUDIASYC Laboratory, University of Technology of Compiègne, France, financed by AUF (Agence Universitaire de la Francophonie) in the framework of *eDalgo* project (March – May 2007)
- Research scholarship at HEUDIASYC Laboratory, University of Technology of Compiègne, France, granted by the Romanian Ministry of Education and Research (MEdC - CNBSS) (March – May 2006)
- Erasmus/Socrates scholarship at HEUDIASYC Research Laboratory, University of Technology of Compiègne, France (March 2005 – May 2005)

- Performance scholarship for remarkable results during the master studies, granted by the University of Craiova (2005/2006, 2006/2007)
- Performance scholarship for remarkable results during the undergraduate studies, granted by the University of Craiova (2002/2003, 2003/2004, 2004/2005)

Awards

- “Best Poster” Award at the IEEE EUROCON 2007 conference (Warsaw, Poland, 9-12 September 2007)
- Honor Diploma awarded by the Senate of the University of Craiova, Romania, for the teaching and research activity (on the 60th anniversary of the University – 1 October 2007)

Affiliations

- Member of IEEE (Computer Society, Education Society, Women in Engineering Society) – since 2006
- Member of SRAIT (Romanian Society of Automation and Technical Informatics) – since 2005
- Member of EAEEIE (European Association for Education in Electrical and Information Engineering) – since 2008
- Member of ACM – since 2008

Other professional responsibilities

- Workshop Organizer and PC Chair for the SAINT 2008 International Workshop on Social and Personal Computing for Web-Supported Learning Communities (SPeL 2008), Turku, Finland, 28 July – 1 August 2008.
- Program Committee member: International Workshop on Adaptivity and Personalization in Ubiquitous Learning Systems (APULS 2008) at the 4th Symposium: USAB 2008, Graz, Austria, November 18-21, 2008; International Workshop on Cognitive Aspects in Intelligent and Adaptive Web-based Educational Systems (CIAWES 2008) at the 16th International Conference on Computers in Education, Taipei, Taiwan, October 27 - 31, 2008; 7th WSEAS Intl. Conference on Education and Educational Technology (EDU '08), Venice, Italy, November 21-23, 2008; IADIS e-Society 2009, Barcelona, Spain, February 26-28, 2009.
- Session Chair: 7th IEEE International Conference on Advanced Learning Technologies (ICALT 2007), Niigata, Japan, 18-20 July 2007; International Carpathian Control Conference (ICCC'2008), Sinaia, Romania, 25-28 May 2008; SPeL 2008 Workshop, Turku, Finland, 28 July - 1 August 2008; 7th International Conference on Web-based Learning (ICWL 2008), Jinhua, China, 20-22 August 2008.
- Coeditor of Annals of the University of Craiova, Automation, Computers, Electronics and Mechatronics Series, Vol. 3 (30), No. 2, Universitaria Press, Craiova, Romania, ISSN: 1841-0626, 2006.

- Reviewing activities: International Journal of Software Engineering and Knowledge Engineering (IJSEKE), ICIC 2007, 2008 (International Conference on Intelligent Computing), IEEE Africon 2007, WSEAS International Conference on Artificial Intelligence, Knowledge Engineering and Databases (AIKED '08), FIE 2008 (The 38th Annual Frontiers in Education Conference), Knowledge Generation, Communication and Management (KGCM 2008), American Computing Conference 2008 (ACC '08)
- Member of the International Organizing Committee of the 9th International Carpathian Control Conference (ICCC'2008), 25-28 May 2008, Sinaia, Romania.
- Member of the Local Organizing Committee for the International Symposium on Intelligent and Distributed Computing - IDC'2007, 18-19 October 2007, Craiova, Romania.