Adaptive learning in the educational e-LORS system: an approach based on preference categories

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Abstract: In the field of electronic education, the recommendation of contents with higher levels of relevance may potentially attract the students' attention. In this context, this work considers students' learning styles, delineated with structured questionnaires, as a means of selecting the best content as for the learning-teaching process. The goal is to present a complete systematisation – the e-LORS system, which is able to recommend electronic educational content based on the relationship between detected learning styles and stored learning objects. Our contributions include the e-LORS system – its multiple-criteria architecture and study case, the methodology based on the Felder-Silverman learning style model and on the IEEE learning object metadata (LOM), and the reporting of experiments conducted in an actual educational context.

Keywords: adaptive learning; educational system; preference categories; recommender system; learning objects; LOM standard; learning profile; learning model; Felder-Silverman learning style model.

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1 Introduction

The personalisation of e-learning environments according to the students' preferences has been a widely discussed theme. The goal is to supply the students with services and information that will comply to their learning styles during learning-teaching activities. In this sense, the main method in order to identify pertinent features concerning the process of content suggestion is the description and the use of learning profiles. Learning profiles may determine how the students interact and react in an environment reflecting their preferences during learning. Learning profiles report the students' particular characteristics to organise, receive, process, remember and thinking when solving a problem. In order to describe learning profiles, it is necessary to use a structured convention so that the organisation of the students' information is done consistently, concisely and embodying their learning styles. In the literature, such conventions are referred to as learner models, constructions that permit that the modelling of the students be used by e-learning systems. With the adoption of a learner model, e-learning systems can adapt themselves according to the students' preferences. This process is based on the use of the metadata contained in the students' profiles so that the selection of content is performed systematically. Once the system is adjusted to preferences described in the profiles, it will retrieve learning content satisfying the students' needs. The use of a learner model can also improve the reuse of content throughout different learning areas.

The adoption of recommending techniques enables the learning system to provide the students with suitable content according to their actual needs. The linking between the content and the student learning profile, considering the learner preferences, may enhance the adequacy of the learning objects that will be offered to the students. As so, the goal of this paper is to present an electronic content recommendation methodology based on the binding of learning profiles and learning objects. In our work, the student learning profile is sorted out through categories that identify the students' learning preferences according to a set of well-defined dimensions. In order to suggest the most appropriate learning objects to the students, the system checks out the relationship between the categories of the model and the characteristics of the objects stored in the system, investigating the correspondent metadata.

The remainder of the paper is organised as follows. Section 2 overviews the topics of learning modelling and systems. Section 3 discusses automatic recommendation. Section 4 presents our methodology, explaining its architecture and the multiple-criteria filtering process. Section 5 describes the developed prototype and the experiments. Finally, Section 6 presents conclusions and directions for further work.

2 Related works: learning modelling and learning systems

The tracking of information about the students' learning profiles, in order to adjust the behaviour of the system to the needs and to the preferences of the students, is a desirable characteristic of e-learning environments (Silva and Rosatelli, 2006). The elements and traits of the students' behaviour delineate their profiles by highlighting features such as: personal identification, personal and social preferences, learning styles, and knowledge level about a subject (Brusilovsky and Millan, 2007).

Usually, the student information is organised according to learner models that concentrate all the important data about them. Generically speaking, a learner model aims to construct a formal and explicit representation of learner profiles, a modality of student modelling. Student modelling intends to create a representation of the student learning process based on the characteristics of her/his expectations about the system (Gauch et al., 2007). Such models guide the system behaviour, acting as a personalisation mechanism for students' features, capturing their learning styles.

Along this text, the term learner profile will refer to instances of a learner model; meanwhile, the term learner style will refer to specific students' characteristics intrinsic to a learner profile defined according to a learner model.

2.1 Learning models, profiles and styles

By means of interviews, or during monitored interaction, the students produce evidences about their learning styles. These learning styles involve the strategies that a student tends to frequently apply while in learning situations (Felder and Silverman, 1988). Different students fit different styles, what makes them adopt attitudes and behaviours that repeat in different moments and configurations (Stash et al., 2004; Tarpin-Bernard and Habieb-Mammar, 2005).

Learning styles are cognitive, affective and psychological traits that determine how a student interacts and reacts in a learning environment (Felder and Silverman, 1988). The idea is to identify the outstanding characteristics that define the learning process of a given learner. To satisfy a given learning style, the teacher must use teaching strategies that will meet the needs of different learning perspectives. The learning style is a component that aids the e-learning system so that it can adapt itself to reflect the features of the student learning profile (Stiubiener et al., 2007).

Table 1 Learning style models

Learning style model	*Observed dimension*	*Features*
Myers-Briggs type indicator (MBTI) (Soles and Moller, 2001)	Extraversion/introversion Sensing/intuition Thinking/feeling judging/perceiving	For each dimension, there is a dominant feature that characterises the learning style.
Kolbs experiential learning model (Lu et al., 2007)	Divergent = Sensing + Reflexive Assimilative = Intuitive + Reflexive Convergent = Intuitive + Active Accommodative = Sensing + Active	The student is classified in one dimension.
Honey and Mumford (2006) learning styles questionnaire (LSQ)	Activist Reflector Theorist Pragmatist	The model summarises the learning style in four categories connected to the learning phases.
Herrmann brain dominance instrument (Bunderson, 1985)	Theorist Organiser Innovator Humanitarian	The brain hemisphere has social influence (parenting, teaching, life experiences, and cultural influences) and not genetic inheritance.
Felder-Silverman learning style model (Felder and Silverman, 1988)	Sensory/intuitive Visual/verbal Active/reflective sequential/global	There is a dominant feature for each dimension that characterises the learning style.

Through the observation of learning styles, it is possible to classify the students according to different learning categories. There are several models used in the classification of learning profiles, each of which is suitable for a different learning context. Although there are many learning style models, Felder and Brent (2005) highlight five of them: the Myers-Briggs type indicator, Kolb's experiential learning model, the Hermann Brain dominance instrument, the Honey and Mumford's (2006) learning styles questionnaire, and the Felder-Silverman learning style model, all of them presented in Table 1.

Myers-Briggs type indicator states that an individual has thinking and acting preferences strongly connected to her/his personality. The model assumes that, when the mind is active, there are some mental operations, such as keeping and organising information (Coffield et al., 2004). According to Soles and Moller (2001), the individual styles are arranged into four bipolar-pair scales, resulting in 16 possible combined psychological types; for instance, a user can have values 'extraversion', 'sensing', 'thinking' and 'perceiving' for her/his cognitive dimensions.

The Kolb's learning style inventory focuses on the knowledge transformation observed in the student experience during the learning process, which has four phases: sensing experience, active experimentation, intuitive conceptualisation and reflective observation. The choices about how to receive (sensing or intuitive experiments) and about how to process (active experimentation and reflective observation) the information can indicate what are the students' preferences (Richmond and Cummings, 2005).

Several experiments were performed by Honey and Mumford aiming at simplifying the Kolb's learning cycle; these efforts produced the Honey and Mumford's learning styles questionnaire. In the questionnaire, each dimension is related to a stage of Kolb's experimental inventory, indicating the strengths and/or the weaknesses of a given individual in specific points of the learning cycle. For instance, a student might have a strong activist trait in the sensing experience (Magoulas et al., 2003). The Herrmann Brain dominance instrument model identifies a student dominant intelligence through the application of a self-assessment questionnaire. The individual preferences are defined by pointing out which brain hemisphere has the strongest influence in the learning process. The other brain hemisphere has a minor participation in the process. Herrmann's model defends the idea that certain combinations of preferences are more harmonious than others. For instance, theorist features usually have consonance with organisation features, but have trouble accommodating humanitarian ones (Coffield et al., 2004).

In an another work, McCalla (2004) proposes the development of e-learning environments based on a methodology called ecological approach, in which the student's information is caught in parallel with his interaction, dynamically updating the student's model. The model is built by the paradigm of active learning. This paradigm works with distributed computational agents, tracking the relevant information found in the interaction context. This process allows the system to cast the construction of learning objects that reflect the students' characteristics. The approach is grounded on a collection of works that includes learning objects reuse, student modelling, data mining, and computational agents. In talking about commercial initiatives, the team management systems (http://www.tms.com.au) is an industry entrepreneurship whose goal is to take user evaluation as a solution to improve the performance in several human activities.

Finally, Felder and Silverman (1988) proposed a model based on dimensions of learning and teaching styles, creating a relationship between learning styles and teaching strategies that can be used to support the students' learning styles. The authors argue that the learning style should be observed by four different behaviour dimensions. We have chosen the model of Felder and Silverman because it aggregates a wider set of desirable features: simplicity, open and wide use, online availability, recognised credibility (Zywno, 2003; Litzinger et al., 2007) and, most important, because its very author suggests it is tailored for engineering.

2.2 Experiments with learning style models

Although the models discussed in the former section have their origins in fields of psychology and pedagogy, they can be used by e-learning systems. In this intent, there are many technological and pedagogical application examples found in the literature.

Diaz and Cartnal (1999) carried out comparative experiences on the application of learning styles following two methods: traditional and web-based electronic learning. According to the authors, the adoption of learning styles improves the student interaction through suitable learning activities.

Soles and Moller (2001) present an e-learning system that uses the Myers-Briggs type indicator as the model to classify the learning style of students. The e-learning environment delivers the activities (materials and tools) corresponding to each student's specific style. The authors emphasise the extraversion type, which demands the presence of groups of people during the student learning interaction, suggesting collaborative activities as important tasks. In a different strategy, Salim and Haron (2006) present a fuzzy logic approach to classify the students, supplying the adaptation mechanism with user learning styles.

Lu et al. (2007) carried out an experience on students learning styles based on Kolb's model. First, the students were asked to solve questions without online help, consulting material, references or, either, other colleagues. The behaviour of the students was tracked and recorded. In a second moment, the students were authorised to access Internet content, such as e-texts, simulation tools, and information exchange with other students through instant messaging. One of the conclusions was the increase in the students learning rates observed during the second situation, demonstrating the importance of online interaction. Honey and Mumford's learning styles questionnaire (http://www.peterhoney.com/) was employed by Lowery (2009). The assessment phase was conducted with the offering of activities, and with the identification of students' styles. The author reports the problems in assisting some styles in disciplines with practical nature, bringing new challenges to future online lectures planning. Lumsdaine et al. (2005) worked with on-campus and off-campus students, watching not only learning features, but also cultural features, supported by the Herrmann Brain dominance instrument model. Basically, students and teacher communication were made by e-mail, or by telephone in on-campus group. Some students became dependent on the teacher guidance, evidencing the need for communication techniques in other similar experiences.

Gomes et al. (2007) report the teaching of a programming language involving students with learning problems. An e-learning system supports the students' interaction by suggesting learning content. The experiment connected the students' learning styles to their difficulties on solving programming problems. The authors identified a severe problem in reading and interpreting the text so that, whenever possible, films and figures were used. The authors concluded that the relation between learning styles and students' learning problems helped the teaching process by selecting a great number of different learning channels.

Stash et al. (2004) presented an authoring tool to design the relation between instructional content and medias by building a graphical model that was incorporated by the AHA! platform. The learning style conceptions of the tool were based on the Honey and Mumford model. A variety of learning object options, related to specific contents, was linked to the students' possible styles; this linkage guided the sequence of content visualisation (prerequisites). The tool translates the graphical design to rules that reflect what actions should be performed according to the student learning needs.

Graf et al. (2008) present another methodology aimed at the identification of learning styles based on student behaviour. In their work, an e-learning system is the source for the collection of student interaction data, which are compared to behaviour patterns previously defined in conformance to the Felder-Silverman learning style model. The authors applied the Felder and Silverman questionnaire (Soloman and Felder, 2008) in order to identify students' profiles. The focus of their work is to evaluate their results with a technique of behaviour patterns matching, verifying the convergence of their experiments.

2.3 Comparison to related works

The works presented in the former two sections presented relevant experiences about the use of models for characterising learning styles. It was possible to observe that the models are normally used for specific teaching domains, as done by Soles and Moller (2001), Lu et al. (2007), Lowery (2009) and Gomes et al. (2007). In another line, the work introduced by Stash et al. (2004) presents the use of learning profiles for content recommendation, however, the relationship between learning objects and learning profiles is not done automatically, what demands that the tutor be responsible for linking objects and profiles.

In the work of Graf et al. (2008), the authors present a methodology that proposes the use of the Felder-Silverman learning style model based on the evaluation of the actions and of the behaviour of the students in an e-learning system. They demonstrate that their line of work can be used through different learning domains. The work of McCalla (2004) reports the joining of several different projects on the problematic of profiles identification and on the problematic of linking these profiles with learning objects. McCalla also reports about project LORNET, a Canadian initiative on the field of learning objects. One of the goals of the project is the adaptation of the learning objects so that they can satisfy to the students' profiles at the same time that they can be reused in later situations.

In the present work, we have raised up a system that links learning objects and learning profiles in automatic fashion. To do so, we use the Felder-Silverman learning style model along with the IEEE learning object metadata (LOM) standard – detailed in Section 4, a combination proposal that, extending former works, can suitably relate profiles and content, automatically, in different fields of learning, and consistently reflecting the intrinsic style of the students. Another point, presented in this work is the multiple-criteria-filtering methodology that, through modules with different responsibilities, selects the learning objects according to three criteria: concept, profile, and technology. The use of multiple criteria allows that the process of retrieving learning objects will not only satisfy the students' needs in different disciplines, but also the technological issues of specific platforms. Compared to the other works reported in this section, our work has put together an ensemble of well-established methodologies in an innovative system; a system capable of a versatile recommendation of learning objects, consistently, structured and reproducible according to well-defined conventions.

3 Automatic content recommendation

The user's satisfaction with the items recommended by an e-learning system is fundamental in order to achieve the user approval; such satisfaction depends both on the quality of the recommendation as well as on the quality of the information – to the scope of this work, we assume high quality content. For the intent of recommendation quality, the relationship between the user and the system is built upon the tracing of personal preferences, reproducing the users' expectations. Hence, user profile is one of the most important components of recommendation systems, storing the relevant data about user preferences (Cramer et al., 2008). We remind that there are different alternatives for educational systems adaptation, what can be based on content only, on presentation only, or on content and presentation; we emphasise that our work, and related discussions, consider adaptation based on content only.

3.1 Techniques on recommender systems

A common use case of recommendation system is: trace the users' tastes, by means of questionnaires or monitored interaction; build profiles about the users, representing their preferences; design a system that uses these profiles to suggest learning objects in accordance to the users' learning needs. In this scenario, the suggestion of learning objects is done by a diversity of recommendation approaches: rule-based filtering, collaborative filtering, content-based classifier, or hybrid combinations of these techniques.

The most common approach is collaborative filtering, which implements the nearest-neighbour model, matching the user's tastes to other existing user samples in the system. The filtering algorithm provides the personal recommendation and determines the option for a group of people with similar preferences and interests (Romero et al., 2007). Briefly speaking, the algorithm considers a person's topic (or topics) request and then selects a subgroup of people whose preferences are similar according to the preferences previously registered. Normally, there is no intervention of the target person. The mechanism rates options out by calculating the subgroup's preference (Herlocker et al., 2004).

It is important to note that the content-based approach concerns the content rather than the users. To do so, it learns about the most relevant content based on the features derived from the objects that the user has accessed (Bilgic, 2005; Burke, 2002). Before suggesting topics, the algorithm focuses on comparing the users' previous preferences and the searched item. The searchable items are characterised by attributes that describe their features, aiding the filtering mechanism in the task of retrieving and presenting useful learning content, even for items previously unseen or unrated by the user (Pazzani and Billsus, 2007).

In other lines of work, Wang et al. (2009) use metadata and ontology theory as solutions to sort out semantic terms in relevant documents or objects during the filtering. The mechanism seeks the content based on its metadata and delivers information to the user. Bilgic (2005) proposes an advanced content-based classifier method; they use the keyword style explanation approach, which explains to the user how the system achieves the suggestions presented on the screen. This approach may increase the likelihood of the recommendations' acceptance by the user.

Rule-based filtering, in turn, is manually or automatically designed by those that have a strong correlation with a domain area, as e-business for instance. The techniques allow the rule's designer to heavily control the adaptation process. The user profile depreciation over time is one of the disadvantages of the technique (Mobasher, 2007).

3.2 Educational recommender systems

Recommender systems, with educational focus, follow the ratings that the students confer on learning strategies, or on learning contents. These systems track such ratings by structured profile delineation questionnaires, or by monitoring the explicit and implicit actions of the students over the system. These data are then analysed in order to automatically suggest the content during the learning process. The user tracking process may occur in many ways, for example, by the use of the Soloman and Felder (2008) questionnaire, or by the observation of the content pages accessed by the student in specific moments (Felfernig et al., 2007; Romero et al., 2007).

The characterisation of the dialogue between the student and the system is crucial to analyse the learner preferences. In this sense, the modelling of the observation process is fundamental to avoid the lacking of relevant information about the student interaction. This dialogue should provide both the user and the system with high-quality information improving the recommendation methods (Cramer et al., 2008). Atif et al. (2003) provide a flexible framework for modelling object-based e-learning environments; authors depart from the premise that the general learner's modelling is an intractable problem and, as so, they use learning routes [or paths (Karampiperis and Sampson, 2005)] as a heuristic in order to maximise the benefits of modelling. In another work, Stoilescu (2008) investigates how intelligent agents can be used in order to adapt learning objects to the students' characteristics. In the same line, Baldiris et al. (2008) present ADAPTAPlan, a system that aids on design by means of user modelling, planning, machine learning, and pervasive use of educational specifications and standards. Finally, Popescu (2010) surveys latest trends on learning styles technology along with a related case study.

4 E-learning object recommender system (e-LORS)

One of the goals of e-learning systems is to offer educational content that is more adequate to each student's specific learning style. In most of the cases, this educational content is referred to as learning objects (LOs). A learning object can be defined as an entity to be used in the learning-teaching process. Within the scope of e-learning, the aim is to create content in digital formats that can be reused for different learning objectives, or even employed in the construction of other learning objects (McGreal, 2004; Milosevi et al., 2007).

One of the ways to organise learning objects, so that they can be used and reused systematically, is through the description of LOs with the aid of metadata. Metadata refers to a set of attributes that describes a learning object in the context of e-learning. The LOM standard of the Institute of Electrical and Electronics Engineers – IEEE is the most commonly metadata specification used in the area of learning objects. The LOM standard (IEEE LOM, 2002) has a structure that describes learning objects through descriptor categories that detail the characteristics of a given learning object. Each category has a specific purpose, such as describing general attributes, or educational goals. The use of a standard as LOM may propel the building of e-learning scenarios. This is possible because the standard is able to support the tracking of the relationship between the LOs and the students' preferences.

Based on concepts of recommender systems and on the LOM standard, this work describes the architecture and the experimentation of the e-learning object recommendation system (e-LORS). The e-LORS system employs concepts of automatic content recommendation according to content selection based on a multiple-criteria filtering methodology. It suggests learning objects, organised according to the LOM standard, based on the observation of the following criteria: concepts of interest, students' learning profiles, and technological issues of a specific environment. The next subsections will report the elements of our proposal and the e-LORS architecture.

4.1 Learner model

The learner model is a fundamental element in recommendation systems. Learner models choose and provide e-learning content by verifying particular information about a specific student, comparing this information with recommendation requirements. They are elements with direct influence over the identification of the students' most adequate content and interaction preferences. The present work adopts the Felder-Silverman learning style model to support the definition of learning profiles. This model was chosen because of its close relationship to learning styles and teaching strategies, resulting in a fruitful combination of these aspects (Felder and Silverman, 1988).

Based on the Felder and Silverman learning style model, we split the students' preferences into categories stored in learner profiles, one profile per student. The goal is to identify a cluster of preferences that reflects different learning perspectives observed in a systematic manner. As shown in Table 2, besides the learning style-category connection, each category has also a teaching-method link that matches the learning styles found in the process of profile definition. We note that dimension sequential/global of the Felder and Silverman was not used as it would demand historical data processing, which is out of the scope of the present work.

Table 2 Felder-Silverman learning style model in the form of preference categories

Preference categories	*Features*	*Learning styles*	*Teaching methods*
Perception	The focus is in the best way through which the student can obtain information.	Sensing intuitive	Concrete abstract
Presentation	It is related to the input. Content preferences chosen by the student such as media types.	Visual verbal	Visual verbal
Participation	It describes the student attitude either as active or reflective.	Active reflective	Active passive

Student personal information, preference categories (learning profile), and technological issues are the elements described in the learner model used in this work. Table 3 presents this model highlighting the components that directly influence the student learning profile identification. The preference categories element concern different dimensions of the students' learning behaviour in an e-learning system. This model is the basis of the recommendation system that we describe in the following sections.

Table 3 Proposed learner model – specification of the students' learning profiles

Component	*Attributes*	*Characterisation*
Personal information	Student identification Name school level	Personal information includes student data that is rarely modified.
Preference categories – refer to Table 2	Perception Presentation Participation	Holds the learning profile in different dimensions through the preference categories specification.
Technology	Technological issues	This aspect describes the characteristics of the learning system, allowing the system to provide content adequate to the technical circumstances of learning. Constraint examples are network connection and operating system.

4.2 e-LORS architecture

The architecture of e-LORS consists of three main modules: concept-based filtering, learning-profile-based filtering and technology-based filtering, as illustrated in Figure 1. In the figure, one can see how e-LORS integrates to an e-learning system as a background system that makes use of the data stored in the learning system. While confronting and handling the content theme (concepts of interest) requested by the student, the system also uses the learning profiles (preference categories) of the students, and the technological constraints of their system in order to recommend appropriate learning objects. The system has a flexible architecture, potentially allowing a variety of e-learning systems to adopt it according to the specificities of each system – see Section 4.2.4.

The recommendation process starts at method getRecommendationLOs, defined in the e-LORS programming interface, and fired by the course management system. This method requires parameters that relate the recommended LOs to the content. These parameters are named 'theme', that is, a set of one more words that are compared to metadata fields stated by the IEEE LOM standard, used to describe the LOs. As a result of method getRecommendationLOs, e-LORS suggests a set of recommended LOs according to three filtering processes: concept-based, learning profile-based, and technology-based. Each learning object is recognised by an Identifier field (LOM general category) according to which the correspondent LOs, retrieved from the LOM repository, are organised as a result set. This result set, then, is used to build the learning workplace that satisfies the student's needs. Next, we review each of the three filtering processes, each of which contextualised in Figure 2.

Figure 1 The architecture of e-LORS' and its integration with an e-learning system (see online version for colours)

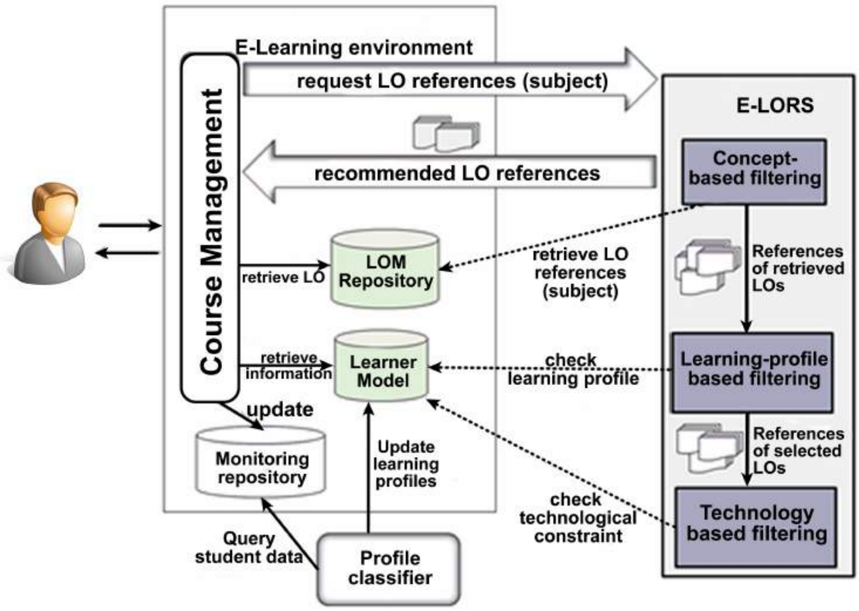
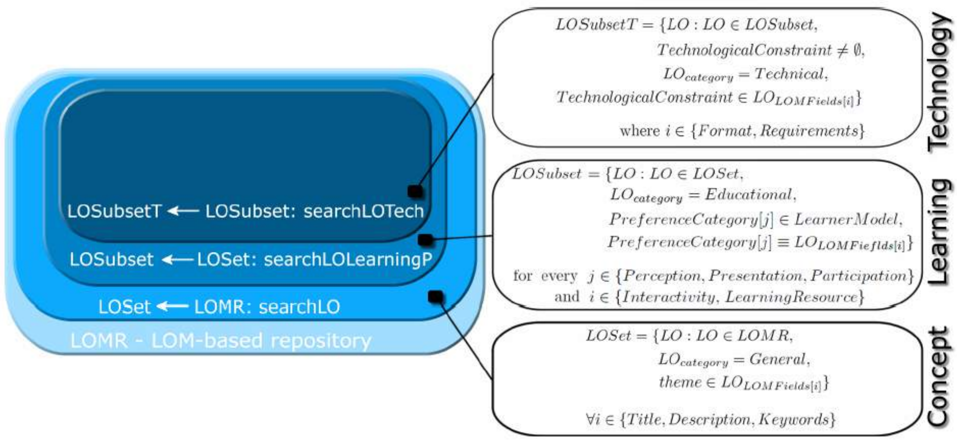


Figure 2 Set diagram corresponding to e-LORS' content filtering (see online version for colours)



4.3 Concept-based filtering module

This module performs the first step of filtering, when e-LORS selects only the LOs that comply with the concepts that a given student is interested on. To do so, the system uses LO metadata, trying to match desired concepts with descriptive concepts. As soon as e-LORS receives the requisition for a recommendation process, it starts the concept-based filtering by searching the LO references in the LOM-based repository

(LOMR). According to the theme, defined from one or many words that are passed as parameters to the system, the filtering is performed. The searchLO method seeks for learning objects that match the theme parameters according to the fields of title, description and keywords, which belong to LOM's general category. This filtering is formally defined by equation (1) and by Predicate 2. The method returns a set of LO identification references (LOSet) that fit the theme.

$$searchLO : LOMR \rightarrow LOSet \tag{1}$$

$$LOSet = \left\{ LO : LO \in LOMR,\, LO_{category} = General,\, theme \in LO_{LOMFields[i]} \right\} \tag{2}$$

$$\forall i \in \{Title,\, Description,\, Keywords\}.$$

4.4 Learning profile-based filtering module

After the concept-based filtering step, e-LORS proceeds with the filtering based on learning profiles, performing it only over the first outcome of references (LOSet) achieved in the concept-based step. This step emphasises the profiles of the students, bringing learning relevance to the system. In its current implementation, the definition of the students' learning profiles is based on the questionnaire of Soloman and Felder (2008). This questionnaire provides information that reflects the Felder-Silverman learning style model, as described in Section 4.1. In e-LORS, this information becomes part of the students' learning profile as fields that describe the preference categories – listed in Table 3.

Table 4 Description of the LOM categories used by e-LORS

LOM category	*LOM field*	*Characterisation*
General	Identifier, type, title, language, description and keywords.	General description.
Technical	Media format (video type, sound), size, physical location, requirements (object use: software version, for example).	Technical features description.
Educational	Interactive type (active, expositive). Learning resource type (exercise, simulation, and questionnaire). Difficulty.	Educational functions and pedagogical characteristics of the learning object.
Relation	Kind of relation between objects. Identification of relation.	Referential data, used for relating different learning objects.

Table 5 Link between the LOM fields and the educational category

LOM field	*Field values*	*Profile feature*	*Preference category*
Interactive	Active expositive	Sensing intuitive	Perception
Learning resource	Figure, video, film, and others text, sound, and others	Visual auditory	Presentation
Learning resource	Practical exercise, experiment, and others; questionnaire and readings	Active reflexive	Participation

Once a student requests content from the e-learning system, its preference categories, recorded in her/his learning profile, are compared to fields interactive type and learning resource type found in the education category of the LOM standard, see Table 4. Table 5, in turn, presents the coupling of the preference categories and the LOM fields of the learning profile, which are compared during the profile-based filtering. In other words, this step combines information from the LOs and from the students' profiles in order to recommend the most adequate content.

$$searchLOLearningP : LOSet \rightarrow LOSubset \tag{3}$$

$$\begin{aligned} LOSet = \{ & LO : LO \in LOSet,\ LO_{category} = Educational, \\ & PreferenceCategory[j] \in LearnerModel, \\ & PreferenceCategory[j] \equiv LO_{LOMFields[i]} \} \end{aligned} \tag{4}$$

for every $j \in \{Perception, Presentation, Participation\}$ and $i \in \{Interactivity, LearningResource\}$.

4.5 Technology-based filtering module

After considering the students' learning profiles, e-LORS carries out the last step of filtering: technological issues. Technological issues refer to possible constraints as, for instance, video formats, software versions, and network bandwidth, when considering LOs for presentation. The goal is to make the user experience more pleasurable, avoiding delays, and software incompatibility. The searchLOTech method receives a dataset outcome from the profile learning-based filtering step, the LOSubset, as a parameter to achieve the final LO subset. With this dataset, it verifies the technological constraints in the learner profile before the final selection of recommended LOs. The new subset (LOSubsetT) is in compliance with the technological characteristics presented by the e-learning system, as formally specified by equation (5) and by Predicate 6.

$$searchLOTech : LOSubset \rightarrow LOSubsetT \tag{5}$$

$$\begin{aligned} LOSubsetT = \{ & LO : LO \in LOSubset, TechnologicalConstraint \neq \emptyset, \\ & TechnologicalConstraint \in LO_{LOMFields[i]} \} \end{aligned} \tag{6}$$

where $i \in \{Format, Requirements\}$.

4.6 e-LORS requirements

An e-learning system must satisfy some requirements in order for it to integrate with e-LORS:

- LOM standard: the adoption of the LOM standard in the storage and management of LOs. This is because the recommendation mechanism works over the connection between LOM and the set of preference categories. The standard presents a great number of fields and e-LORS considers many of them during the recommendation (Zaina and Bressan, 2009). Table 4 lists the LOM standard and its respective fields (IEEE LOM, 2002) as what are used by e-LORS.

- Preference categories: if the e-learning system uses any kind of learner model, it may be necessary an extension to aggregate the profile element based on preference categories. Questionnaires and preference forms may support the system in the delineation of preference categories, updating the categorisation in conformity to the students’ answers. Another option is to monitor the students’ interaction and compare it to previously known profile models, just as proposed by Zaina and Bressan (2008), who describes the insertion of a classifier system to support the identification of learner preferences.
- Technology: the technology description, although desirable, is optional. It is mainly used when there are technological limitations in the target learning management system.

5 System e-LORS prototyping and validation

We have implemented a prototype of e-LORS that was used in three regular college courses: Computer Engineering Data Structures (50 students), Electrical Engineering Physics I (150 students), and Civil Engineering Physics I (147 students). The courses are part of the graduation curricula from Brazilian University Faculdade de Engenharia de Sorocaba (FACENS). No specific course management system was used, but an *ad hoc* institutional system integrated to e-LORS. This system, along with e-LORS, was used as a supplement to traditional lectures attended by a total of 347 students.

5.1 Delineation of student profiles

The profiles of the 347 students that took part of the experiment were established according to Table 3. Personal data were imported from a previously stored institutional dataset. Technology data were not considered for this first experiment. The Preference Categories were determined with the use of the online questionnaire of Soloman and Felder; the questionnaire data, which reflects the Felder-Silverman learning style model, were translated into preference categories, just as proposed in the architecture of e-LORS.

Table 6 presents the profile types recognised after the application of the questionnaire. Six combinations of preference categories were identified: intuitive-verbal-reflexive, intuitive-visual-reflexive, intuitive-verbal-active, sensing-verbal-active, sensing-visual-active and sensing-verbal-reflexive, each one corresponding to a distinct learning style. Figure 3 presents the distribution (in percentage numbers) of learning styles according to the preference categories for each college course considered in our experiment. In the figure, it is possible to see that the sensing-verbal-active style was the most frequent one for data structures, answering for 68% of the profiles categorisation. Meanwhile, the sensing-visual-active style was the most frequent one for Physics I, answering for 70% of the observations.

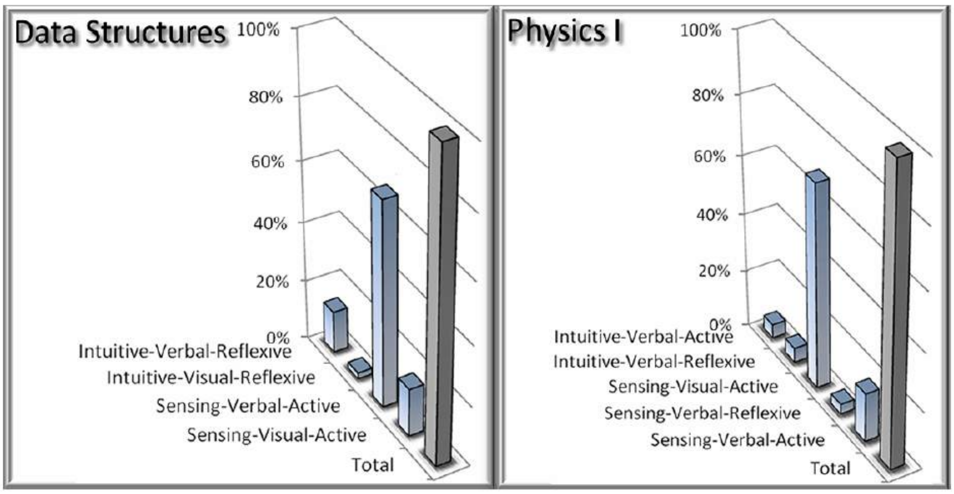
Considering both charts, one can see that sensing for the perception category, and active for the participation category were the predominant characteristics, providing an idea of how engineering students behave. According to Table 2, such students adhere to concrete and active teaching methods, which correspond to LOs related to real-world settings, problems modelling, and study cases. It is possible to see, as well, that for the presentation category, the students differ on verbal, for data structures, and visual, for

Physics I. We suppose that this disparity comes from the fact that, while data structures are strongly related to programming languages, physics is strongly related to analytical exercises. Therefore, students from the former course rely heavily on verbal explanations of higher-level concepts – such as computer commands; and students from the later course rely on the observation of analytical formalisms (such as equations, proofs, and solved exercises), a visual activity.

Table 6 Profile types (learning styles) identified with the application of the questionnaire of Soloman and Felder

Profile type	*Perception*	*Presentation*	*Participation*
A	Intuitive	Verbal	Reflexive
B	Intuitive	Visual	Reflexive
C	Intuitive	Verbal	Active
D	Sensing	Verbal	Active
E	Sensing	Visual	Active
F	Sensing	Verbal	Reflexive

Figure 3 Students' preference categories for data structures and Physics I courses based on the outcome of Soloman and Felder (see online version for colours)



5.2 Learning objects cataloguing

In order to test our system, we have catalogued several learning objects for the topics on data structures and physics what allowed us to attend different learning styles during the experience. A crew of professors and assistants were designated to create the LOs at the same time that they were catalogued for further use by e-LORS. The professors were responsible for planning the LOs so that they would carry metadata in accordance to the LOM standard and to the Felder-Silverman learning style model in the shape of preference categories. This way, the LOs would fit both the concept-based, and the learning profile-based filtering modules of e-LORS. The assistants helped up in the task and raised a LOM-based repository over which the whole system would work. For the data structures course, the crew of professors and assistants catalogued 150 learning objects – corresponding to 6 lessons; for the Physics I course, the crew catalogued 80 learning objects – corresponding to 7 lessons. Some examples of the objects that were catalogued are: demonstration simulations, interactive simulations, explaining texts, figures and case studies.

5.3 Experimentation in an actual educational context

After the delineation of the 347 student profiles considered for the experiment and after the cataloguing of a substantial number of LOs, we could raise a system consisting of a LOM repository, and a learner model structure. These two elements allowed us to integrate the e-LORS prototype to an institutional ad hoc e-learning system. The whole configuration – e-LORS and e-learning system – were, then, put into production during two academic semesters. During the first semester, students from Computer Engineering Data Structures used the system throughout their course term. For the second semester, students from Electrical and Civil Engineering Physics I used the system.

During the system experimentation, the results were different for each group of students. For the data structures group, e-LORS recommended content mostly characterised by textual descriptions and lectures videos (with verbal communication). Differently, for the physics groups, e-LORS recommended content mainly characterised by analytical exercises and images. This was previously expected because the analysis of the preference categories, as explained in Section 5.1, pointed out that each course had a different characterisation for the presentation category. Also expected was the fact that both courses received recommendations for problems modelling and study cases, reflecting their common preferences for categories perception and participation.

The final step of the experiment was the evaluation of the students' perception of the system. To do so, an evaluation form was posed for the students who had to indicate their satisfaction in a 1 to 4 score scale, 1 for totally non-satisfied and 4 for completely satisfied. For the data structures course, the students summed 76% of complete (score 4) or almost complete satisfaction (score 3). For the physics course, the students summed 67% of complete (score 4) or almost complete satisfaction (score 3).

5.4 The e-LORS prototype in action

When in the e-learning system used in our experiments, e-LORS initially searches for and configures the LOM repository and the learner model structure. After that, the recommendation process initiates when e-LORS receives parameters for a theme, which will indicate what the next search subject is. The domain of possible theme parameters is determined by the process of LOs cataloguing, hence there is a limited set of possible requisitions that a student can submit. As an example, following we report an operation in which the theme graph representation is submitted to e-LORS as the topic of interest of a student from the data structures course having learning style sensing-visual-active. After receiving the theme, e-LORS proceeds by searching the LOM repository and it is expected that the system will provide material adequate for graph representation and for style sensing-visual-active, as follows:

- Step 1 – concept-based filtering: seeks and selects for all the LOs descriptions likewise graph representation. This step uses the LOM general category data – refer to predicate (2). In our experiment configuration, e-LORS identifies ten different learning object identifiers. This set, the LOSet, is sent as a parameter to the next step of filtering.
- Step 2 – profile learning-based filtering: over the LOSet generated in Step 1, this step seeks and selects for all the LOs whose metadata matches style sensing-visual-active. This step uses the LOM educational category and the preference categories of the learner profiles – refer to predicate (4). System e-LORS, then, identifies a lecture video and modelling exercises.

Finally, the presentation is built using the learning objects that were selected, allowing the student to make her/his own choice.

5.5 Analysis and ongoing works

The implementation of the e-LORS architecture demonstrated that the methodology of multiple-steps filtering is adequate in the task of content recommendation. This approach permits that several needs, found in the learning process, can be progressively considered. In e-LORS, factors concept, learning profile and technology are part of the content selection, endowing the system with a wide amplitude of criteria during the recommendation process.

After a first period of experimentation with courses Physics I and data structures, the impact of e-LORS was verified considering 1,309 students from Physics I and Physics II courses, which are common to all of the under graduation students of FACENS university. To do so, we have verified the average grade of the students before (year 2007) and after (year 2008) using e-LORS. In 2007, a total of 675 students did not make use of the system reaching an average grade of 5.8 with a standard deviation of 2.2. In 2008, a total of 715 students benefited from the system reaching an average grade of 6.0 with a standard deviation of 2.0. Within this universe of 1,309 students, the increase of the average grade is considered significant; we explain this impact as a result of including the students in the experiment, what led them to use a more accessible e-learning system. We also consider that the e-LORS methodology has impacted the process because students at FACENS have long-term used a previous proprietary e-learning system; this system is merely a repository of learning objects, not providing any kind of recommendation. System e-LORS was a shift in the manner that students access learning objects.

Supported by the results obtained in the experiments, the team of professors and assistants from the physics course has been working since then in the cataloguing of more LOs. This work intends to augment the scope of content available to the students, satisfying a larger scope of learning profiles. The goal is to verify whether the larger diversity of LOs can determine a higher level of satisfaction and of performance.

6 Conclusions

The offering of educational materials matching the students' learning profiles supports the learning-teaching process by aiding the students with content that suits their learning styles. In this context, this paper proposed a methodological systematisation, the e-LORS system with preference categories, a configuration that is able to suggest learning objects concerning the students' learning styles. In our work, we have designed a learner model that sorts out the learning profiles in different dimensions and in accordance to several aspects. The core of our model is the use preference categories as descriptive metadata for learning styles. The Felder-Silverman learning style model was used as the basis for the learning style description.

The linking of the preference categories reported in the learner model and the learning objects description categories of the IEEE LOM standard was another important point under discussion. This linking was possible due to the adherence between the students' learning profiles and the available learning objects according to our learner model in a process of metadata binding. Such biding was accomplished with the aid of the broadly adopted LOM standard, providing universality to our work. A prototype of system e-LORS was developed and experimented along two academic semesters with 347 students from three engineering courses. The results demonstrated the accuracy of the e-LORS content selection and, also, the satisfaction of the students during their academic activities.

Further works include ubiquitous learning – which aims at adding new features to the recommendation component, and the use of portable devices – what demands the consideration not only of the learning style but also of the context of interaction (technological issues). The problematic of using portable devices embodies characteristics such as screen size and available memory, features that must be considered when choosing the most adequate content.

References

Atif, Y., Benlamri, R. and Berri, J. (2003) 'Learning objects based framework for self-adaptive learning', *Education and Information Technologies*, Vol. 8, No. 4, pp.345–368.

Baldiris, S., Santos, O.C., Barrera, C., Boticario, J.G., Velez, J. and Fabregat, R. (2008) 'Integration of educational specifications and standards to support adaptive learning scenarios in adaptaplan', *International Journal of Computer Science and Applications*, Vol. 5, No. 1, pp.88–107.

Bilgic, M. (2005) 'Explaining recommendations: satisfaction vs. promotion', in *Proceedings of Beyond Personalization 2005, the Workshop on the Next Stage of Recommender Systems Research (IUI2005)*, pp.13–18.

Brusilovsky, P. and Millan, E. (2007) 'User models for adaptive hypermedia and adaptive educational systems', in *The Adaptive Web, Lecture Notes in Computer Science*, Vol. 4321, pp.3–53, Springer, Berlin.

Bunderson, C.V. (1985) 'Research: the validity of the Herrmann brain dominance instrument', Master's thesis, Herrmann International.

Burke, R. (2002) 'Hybrid recommender systems: survey and experiments', *User Modeling and User-Adapted Interaction*, Vol. 12, No. 4, pp.331–370.

Coffield, F., Moseley, D., Hall, E. and Ecclestone, K. (2004) 'Learning styles and pedagogy in post-16 learning. a systematic and critical review', Technical report, Learning and Skills Research Centre.

Cramer, H., Evers, V., Ramlal, S., Someren, M., Rutledge, L., Stash, N., Aroyo, L. and Wielinga, B. (2008) 'The effects of transparency on trust in and acceptance of a content-based art recommender', *User Modeling and User-Adapted Interaction*, Vol. 18, No. 5, pp.455–496.

Diaz, D.P. and Cartnal, R.B. (1999) 'Students' learning styles in two classes: online distance learning and equivalent on-campus', *College Teaching*, Vol. 47, No. 4, pp.130–135.

Felder, R.M. and Brent, R. (2005) 'Understanding student differences', *Journal of Engineering Education*, Vol. 94, No. 1, pp.57–72.

Felder, R.M. and Silverman, L.K. (1988) 'Learning and teaching styles in engineering education', *Journal of Engineering Education*, Vol. 78, No. 7, pp.674–681.

Felfernig, A., Friedrich, G. and Schmidt-Thieme, L. (2007) 'Guest editors' introduction: recommender systems', *Intelligent Systems, IEEE*, May–June, Vol. 22, No. 3, pp.18–21.

Gauch, S., Speretta, M., Chandramouli, A. and Micarelli, A. (2007) *The Adaptive Web. Chapter User Profiles for Personalized Information Access*, pp.54–89, Springer-Verlag, Berlin, Heidelberg.

Gomes, A., Carmo, L., Santos, A. and Mendes, A. (2007) 'Learning styles in an e-learning tool', in *International Conference on Engineering Education*, September.

Graf, S., Kinshuk and Liu, T-C. (2008) 'Identifying learning styles in learning management systems by using indications from students' behaviour', in *Proceedings of the 2008 Eighth IEEE International Conference on Advanced Learning Technologies*, pp.482–486, IEEE Computer Society, Washington, DC, USA.

Herlocker, J.L., Konstan, J.A., Terveen, L.G. and Riedl, J.T. (2004) 'Evaluating collaborative filtering recommender systems', *ACM Trans. Inf. Syst*., January, Vol. 22, No. 1, pp.5–53.

Honey, P. and Mumford, A. (2006) *The Learning Styles Questionnaire, 80-item Version*, Peter Honey Publications, Berkshire, UK.

IEEE LOM (2002) 'Draft standard for learning object metadata', available at http://ltsc.ieee.org/wg12/index.html (accessed on April 2009).

Karampiperis, P. and Sampson, D. (2005) 'Adaptive learning resources sequencing in educational hypermedia systems', *Educational Technology & Society*, Vol. 8, pp.128–147.

Litzinger, T., Lee, S., Wise, J. and Felder, R. (2007) 'A psychometric study of the index of learning styles', *Journal of Engineering Education*, Vol. 96, No. 4, p.309+.

Lowery, C. (2009) 'Adapting to student learning styles in a first year electrical/electronic engineering degree module', *Journal of the Higher Education Academy Engineering Subject Centre*, Vol. 4, No. 1, pp.52–60.

Lu, H., Jia, L., Gong, S-h. and Clark, B. (2007) 'The relationship of Kolb learning styles, online learning behaviors and learning outcomes', *Educational Technology & Society*, Vol. 10, No. 4, pp.187–196.

Lumsdaine, E., Evensen, H.A. and Zenner, P.F. (2005) 'Educating designers on design via distance learning', in *Proceedings of the 2005 American Society for Engineering Education Annual Conference & Exposition*, pp.1–9, Session 1625.

Magoulas, G.D., Papanikolaou, Y. and Grigoriadou, M. (2003) 'Adaptive web-based learning: accommodating individual differences through system's adaptation', *British Journal of Educational Technology*, Vol. 34, No. 4, pp.511–527.

McCalla, G. (2004) 'The ecological approach to the design of e-learning environments: purpose-based capture and use of information about learners', *Journal of Interactive Media in Education*, Vol. 7, No. 1, pp.1–23.

McGreal, R. (2004) 'Learning objects: a practical definition', *International Journal of Instructional Technology and Distance Learning*, Vol. 1, No. 9, pp.21–32.

Milosevi, D., Brkovi, M., Debevc, M. and Krneta, R. (2007) 'Adaptive learning by using scos metadata', *Interdisciplinary Journal of Knowledge and Learning Objects*, Vol. 3, No. 1, pp.163–174.

Mobasher, B. (2007) *The Adaptive Web. Chapter Data Mining for Web Personalization*, pp.90–135, Springer-Verlag, Berlin, Heidelberg.

Pazzani, M.J. and Billsus, D. (2007) *The Adaptive Web. Chapter Content-based Recommendation Systems*, pp.325–341, Springer-Verlag, Berlin, Heidelberg.

Popescu, E. (2010) 'Learning styles in technology enhanced education: latest trends and a case study', in *International Conference on Virtual Learning*, pp.206–213.

Richmond, A.A.S. and Cummings, R.R. (2005) 'Implementing Kolb's learning styles into online distance education', *International Journal of Technology in Teaching and Learning,* Vol. 1, No. 1, pp.45–54.

Romero, C., Ventura, S., Delgado, J.A. and De Bra, P. (2007) *Personalized Links Recommendation Based on Data Mining in Adaptive Educational Hypermedia Systems*, Vol. 4753, pp.292–306, Springer-Verlag, Berlin/Heidelberg.

Salim, N. and Haron, N. (2006) 'The construction of fuzzy set and fuzzy rule for mixed approach in adaptive hypermedia learning system', in *Technologies for E-Learning and Digital Entertainment, Lecture Notes in Computer Science*, Vol. 3942, pp.183–187, Springer, Berlin/Heidelberg, 10.1007/11736639 26.

Silva, G. and Rosatelli, M. (2006) 'Adaptation in educational hypermedia based on the classification of the user profile', in *Intelligent Tutoring Systems, Lecture Notes in Computer Science*, Vol. 4053, pp.268–277, Springer, Berlin/Heidelberg, 10.1007/11774303 27.

Soles, C. and Moller, L. (2001) 'Myers Briggs type preferences in distance learning education', *International Journal of Educational Technology*, Vol. 2, No. 2, pp.1–12.

Soloman, B.A. and Felder, R.M. (2008) 'Index of learning styles questionnaires', available at http://www.engr.ncsu.edu/learningstyles/ilsweb.html (accessed on October 2009).

Stash, N.V.., Cristea, A.I. and De Bra, P.M. (2004) 'Authoring of learning styles in adaptive hypermedia: problems and solutions', in *Proceedings of the 13th International World Wide Web Conference on Alternate Track Papers & Posters, WWW Alt. '04*, pp.114–123, ACM, New York, NY, USA.

Stiubiener, I., Ruggiero, W.V. and Rosatelli, M.C. (2007) 'An approach to personalisation in e-learning', *IEEE International Conference on Advanced Learning Technologies*, pp.189–193.

Stoilescu, D. (2008) 'Modalities of using learning objects for intelligent agents in learning', *Interdisciplinary Journal of E-Learning and Learning Objects*, Vol. 4, No. 1, pp.49–64.

Tarpin-Bernard, F. and Habieb-Mammar, H. (2005) 'Modeling elementary cognitive abilities for adaptive hypermedia presentation', *User Modeling and User-Adapted Interaction*, Vol. 15, pp.459–495, 10.1007/s11257-005-2529-3.

Wang, Y., Stash, N., Aroyo, L., Hollink, L. and Schreiber, G. (2009) 'Semantic relations in content-based recommender systems', in *Proceedings of the Fifth International Conference on Knowledge Capture*, pp.209–210.

Zaina, L.A.M. and Bressan, G. (2008) 'Classification of learning profile based on categories of student preferences', in *Frontiers in Education Conference, 2008. FIE 2008. 38th Annual*, pp.F4E-1–F4E-6.

Zaina, L.A.M. and Bressan, G. (2009) 'Learning objects retrieval from contextual analysis of user preferences to enhance e-learning personalization, in *Proceedings of IADIS International Conference WWW/Internet*, pp.237–244.

Zywno, M.S. (2003) 'A contribution to validation of score meaning for Felder-Soloman's index of learning styles', in *Proceedings of the 2003 American Society for Engineering Education Annual Conference & Exposition*, pp.1–16, Session 2351.