Recommendation Model of Personalized Teaching Materials in E-Learning Environments

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***Abstract*—This full paper of research category presents a proposal for a smart recommendation model to personalize the provision of teaching materials in Virtual Learning Environments (VLE), to continually learn from student feedback. This research presents a model that is divided into 4 parts: 1) Student model; 2) Domain model; 3) Mining module; and 4) Recommendation module. This research contributes to focus on the development of cognitive skills related to learning styles, aiming to help students understand the strengths and weaknesses of their cognitive and objective - cognitive strategies, with the construction of behavioral patterns generated from the exchange of messages information between the student and mining modules. It is hoped that with the implementation of e-learning models, this proposal can contribute to assist in guiding the teaching and learning process towards mastering a curriculum, with interactive regulations, and the acquisition of the corresponding skills through the discovery of knowledge and automation of the recommendation process. Besides, contributing to self-esteem and, mainly, helps to train professionals better prepared for the job market. Our focus is to describe complex processing of recommendations in e-learning environments in terms of knowledge, not the details of its implementation.**

Keywords—recommend model, personalization, virtual learning environment.

I. INTRODUCTION

Following the current trends triggered by the evolution of technology, the education process began to shift from traditional classroom teaching to more modern approaches, e.g., online education. As a consequence, current trends in this area are focused on the design of e-learning systems that contribute to improving student performance during the learning process. The objective is no longer to acquire knowledge alone, but how to provide, through technological tools, the most appropriate form of instruction for each individual.

E-learning has become an essential factor in the modern educational system. With the evolution of the Internet and the maturity of this method, attention is increasingly focused on the development of electronic content that meets the educational objectives required by students. Research in this area has achieved explosive growth in recent years, and numerous personalization proposals for e-learning have been developed. However, the lack of practical experience and the availability of the same teaching materials for all students, are often pointed out as a negative side.

Considering the diverse student population, e-learning must recognize differences in students' personalities to make the learning process more individualized and to help overcome the one-size-fits-all learning model, in which the same learning resources are provided to all students. Supporting quality teaching and learning methods has been one of the critical factors in creating an e-learning course.

The rapid development of Information and Communication Technologies (ICTs) initiates a change from the traditional way of learning to new forms, such as personalized e-learning. The e-learning content is recognized as an important factor in the development of e-learning courses, and it is necessary that it is suitable for the different learning profiles. Personalization is among the main challenges in the field of e-learning, where currently only a few learning environments, especially experimental ones, support these features.

Considering the exposed scenario, and based on the state of the art survey, the importance and need to develop a Personalized Activities Recommendation Model to support students in e-learning environments was identified. The models proposed in this area include models well developed technically, but lacking in the pedagogical aspect.

This article discusses the importance of presenting personalized learning material to suit individuals' learning styles and discusses assessment issues and how to measure the effectiveness of personalized learning systems. The article is organized as follows: this section presented the introduction. Section II presents the background and related works. Section III describes the proposed recommendation model, and to conclude Section IV presents the conclusion and future work.

II. BACKGROUND AND RELATED STUDIES

Personalization of teaching and personalized learning systems have become popular topics in scientific literature during the past few years [1]. According to [2], content personalization is the ability to provide personalized content and services to individuals based on knowledge about their preferences and behavior.

Personalization is defined as everything that refers to the process of matching content, services or products with individuals [1]. The matching process is based on what a company knows about individual users; this information is often referred to as a user profile. The user profile defines the customer's preferences, behaviors and demographics.

The purpose of personalization is to provide relevant content to an individual user, or a group of users based on what is known about them based on their preferences and needs [3]. A personalized recommendation is a mechanism for overcoming the information overload that occurs in new learning environments and providing adequate resources for students.

Our model combines personalization and customization. This is because at the same time that it asks students for information about their learning preferences (customization), it also analyzes and applies data collected on the users' learning style and behavior (personalization). Customization improves the experience because it allows students to select their preferences. By defining what they want, it makes it easier for students to recommend personalized learning objects according to their specific needs.

According to Kolb [4], customization can be seen from two different perspectives:

1) As a customization or selection of just one Learning Object (LO) or a learning scenario;

2) As a selection and composition of a set of them, for example, personalization of a learning scenario, finding a learning path.

The first perspective formulates the LOs selection problem, and the second solves the curriculum sequencing problem [5]. In addition, customization can be done at three levels:

- In the user interface: the interface is adapted according to the user's needs and the context. For example, an interface for a person with visual impairment or without visual impairment will be different.
- In the business processes associated with the applications: these processes can be different depending on the user. For example, the transport document will be different for an identified user and for an occasional user.
- Through content: concerns with personalization are information provided to the user or the number and nature of the functional services available.

Although customization can be done at several levels, some external factors can influence [6]:

- User/Group: This category contains all factors related specifically to users (for example, centers of interest);
- Information: This category contains all factors related to the content;
- Context: This category contains all factors related to the technical and external environment;
- Recovery approach: This category contains all factors related to the choice of method and the tools used to carry out the customization.

This explanation highlights the fact that the concept of personalization itself is a broad field of research, in which technical solutions alone are not capable of solving problems. One of the critical challenges that the e-learning environment faces is information overload. The explosion of information that came with these systems from different sources brought up the problem of finding useful information, as every student has his own preferences and requirements [7].

The ability of users to find the information they want grows more slowly than the rate at which new information becomes available. The use of modern technology to manage and control information can improve the quality of the data presented, as well as the content of that data. A recommendation system's main task is to choose certain objects that meet users' requirements [10].

Recommendation models are constantly being used in a number of areas, where recommendations depend on user history and other data. However, there are still limitations if decision-making is considered in real-time, as users' preferences and skills change overtime very often. Below, we present some related papers to this research.

A customized integrated model for e-learning systems is proposed in Nagori & Aghila [7]. The model is divided into two stages: the first uses the topic modeling technique of Dirichlet's latent allocation to perform the topic analysis; the second introduces a measure of similarity with the content-based recommendation approach. The authors use the content-based recommendation model, trying to overcome the analysis of restricted content, excessive content specialization and a cold start problem.

In the case of the reuse of learning objects (LOs), Soo et al. [8] present a model that recommends LOs to users by querying the input keywords, user preference history and preference history of similar users. However, if a user is new to the system and the system has no user record, the model will recommend LOs only by querying the user's input keywords and the popularity of LOs among all users. The contribution of the research is to help users select and reuse the most appropriate learning objects.

Atallah et al. [9] present a model integrated with the Moodle Virtual Learning Environment (VLE) messaging system to filter out unwanted messages, recommend material (PowerPoint presentation) to students and help them find answers to their questions based on the message. The problem with this research is how to build a model to avoid messages that contain taboo words and send recommended material to students according to their questions. The model results are organized using the vector space model, which sends the highest organization of the material to the student.

A data-driven recommendation model that uses the student's personality and learning style in order to recommend the presentation of the learning course or the way objects are organized is presented in Halawa et al. [5]. The data model identifies the student's personality type and dominant preference based on the Myers-Briggs typology. The proposed model uses data from student involvement with AVA Moodle and the social network Facebook. The predicted personality preference was used to match it with the corresponding learning styles of the Kolb model.

In the case of recommendation methods, Li et al. [11] present a method for recommending e-learning resources based on learning contexts. By building the student's learning context map and the "knowledge-resource" context correlation model, combined with personalized recommendation technology, students are treated with learning resources that meet their learning goals, knowledge capacity and individual preference. The presented strategy can help students to understand the knowledge system and the direction of learning, in addition to improving their efficiency in learning.

In the study by Liou [12], a recommendation method was proposed based on the student's rating for recommending personalized articles in an online forum. In this research, the student can classify the articles that the colleague has posted by the proposed classification mechanism, which is similar to the like button on Facebook. The result of the experiment shows that the proposed method performs well compared to the collaborative filtering method.

A hybrid algorithm for the recommendation of Learning Objects (LO) aimed at students' learning profiles is presented in [19]. The Learning Styles-based Collaborative Topic Recommender algorithm was developed based on the Collaborative Topic Regression (CTR) model. The Learning Style is incorporated into the CTR to predict LO classification. The proposed model controls which classifications are more effective in the students' learning process and which LO recommendations fit better to the student's learning profile.

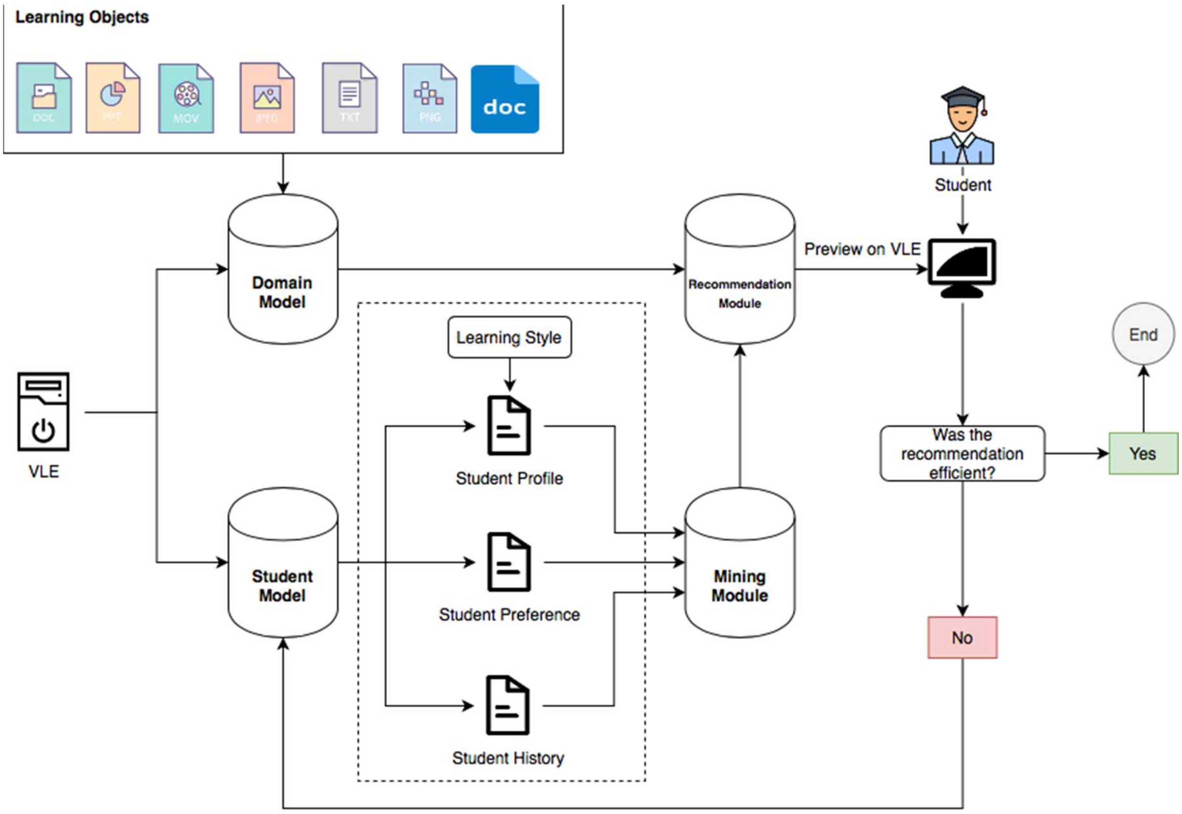

Fig. 1. Functional Architecture.

A teaching customization model based on ELO to recommend learning objects is presented in [20]. The learning objects correspond to programming problems in an online platform for automatic submission and evaluation. The authors observed that students showed greater engagement (in terms of higher frequency of use, higher rate of success and production of positive feedbacks) at the stage when the recommendation corresponded to the proposed model.

In these works, the deficiency in relating research with pedagogical theories of learning is evident, since most of them only the technological aspects are considered. In addition, some important characteristics, such as learning style, cognitive style, skills and competences, and student model, are not taken into account.

In view of the approach of these presented works, the accomplishment of this research brings contribution since educational aspects lack topics of analysis under different approaches. Thus, using a collaborative filter, recommendations for learning objects can be made in virtual learning environments.

III. RECOMMENDATION MODEL

The need to know how students learn is a major concern. Usually the activities and teaching materials are the same for all students, and may end up being insufficient for the effective learning of each one. In general, teachers add material related to the domain of knowledge and also develop pedagogical mediation activities for students.

This process results in a learning environment that presents the same content for all students, without taking into account the differences that exist between each one, both in performance and behavior in the environment [13]. The model presented in this article aims to provide a personalized learning environment, taking into account the different learning styles of students.

The functional architecture is shown in Figure 1, where users (teachers or students) can access the learning environment from any device with access to the internet. The web server stores information about courses, users and teaching materials.

For the recommendation process to take place, the model is divided into 3 parts (as we can see in Figure 2):

- Student model: responsible for storing all students' personal information (student profile, preferences and history).
- Domain model: responsible for storing course information, including learning objects available in the learning environment. The teacher is responsible for inserting these materials in the virtual room.
- Pedagogical model: composed of the mining module and recommendation module.

Student data is captured and recorded centrally in the student model (SM), and learning objects, as well as course information, are stored in the domain model. We propose a recommendation model using collaborative filtering. This technique assumes that users with similar characteristics and behaviors will have similar preferences. With our recommendation model, students are classified into groups and receive recommendations for learning objects taking into account relevant factors and also considering their similarities with specific groups.

A. Student Model

Each student has a different learning style and individual needs, and the contents of the learning environments must be designed centrally in them. The factors that make this content significantly useful, accessible and flexible, fall into four categories [14]: factors related to management, technological factors, pedagogical factors, and the user interface.

The data generated from the student's involvement with the VLE can be used to create a model to predict the student's personality type and dominant preference, so that we can identify the learning style based on the anticipated personality type. The learning style identified will help us to recommend the best learning object for each student, in order to improve the quality of the teaching and learning processes in the e-learning system.

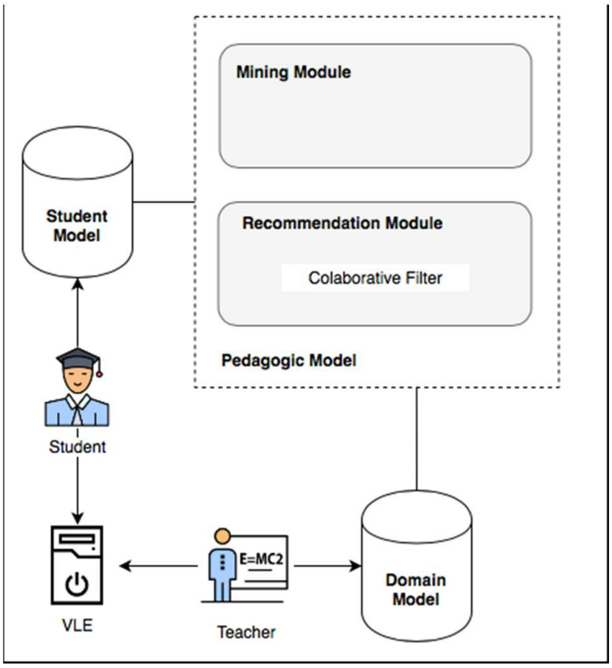

Fig. 2. Modules Organization.

The student model (presented in Figure 3) is responsible for collecting and storing all students' personal information, navigation, test results history, learning styles, preferences, etc. Once the data is collected, they interact with the mining module. Students are modeled according to existing data in the VLE.

Students' personal information are collected with the application of two online questionnaires: Index of learning style [16] to identify students' learning style, and Keirsey and Bates temperament types [17] to identify students' cognitive style.

B. Mining module

Educational Data Mining (EDM) deals with the application of data mining techniques to solve problems in the educational field. With the interpretation of these data, it is possible to outline the student's behavior profile, so that teachers plan which corrective actions should provide a better learning process, and consequently increase performance and a possible reduction of academic dropout.

With the application of EDM, it is possible to develop a customized educational alternative, privileging the strengths such as, the content that generates the greatest number of interactions, and identifying the areas of greatest fragility, thus reinforcing the teaching so that the student reaches a more training uniform and complete.

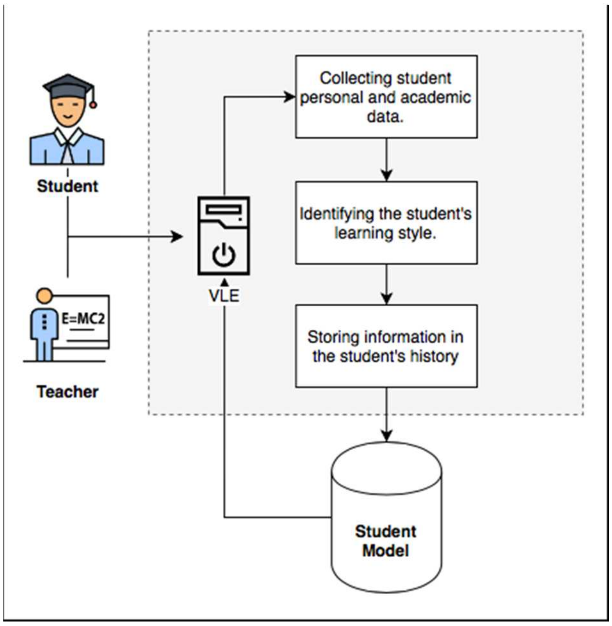

Fig. 3. Student Model.

The mining module of our model is responsible for the customizations that will be carried out. This module analyzes and classifies the information according to the learning styles and cognitive skills identified during the learner's interaction to serve as input to the recommendation module, and is divided into five steps:

- Grouping: groups all student data as shown in the Virtual Learning Environment record (academic data, personal data, information about the course, access information, etc.). In grouping, the objective is to divide the data set into groups, so that the objects contained in the data are naturally grouped according to the similarity between them. The k-means algorithm [18] will be used to group the data of all students. K-means was chosen at this stage, instead of other grouping techniques, due to its ease of use and suitability for the purpose.

- Classification: classifies students according to the skills and competences acquired. The classification task concerns the process of finding a model that describes and distinguishes classes of data or concepts. The models are derived based on the analysis of data collections, called training sets, which correspond to data objects for which the class labels are known. The model is used to predict the class label of objects for which the class label is unknown.

- Association: it seeks to generate/identify if-then rules that allow associating the observed value of one variable with the value of another variable. That is, if a condition is true (e.g. variable Y has a value of 1) and a rule associates that condition with the value of another variable X, then we can infer the value of this variable X. detects the systematic relationships between the variables classified in the previous step.

- Pattern recognition: recognizes students' behavior according to observed patterns.

- Text mining: interprets and evaluates standardized data, to have input data for the recommendation module.

C. Recommendation module

This module is responsible for retrieving the information from the mining module and assessing the capabilities to recommend appropriate resources for the student's profile. The related rules for setting up the student profile are similar to the rules created and implemented according to the online questionnaires that must be delivered to the students at the beginning of the course. The online questionnaire aims to create student profiles and adapt recommendations accordingly.

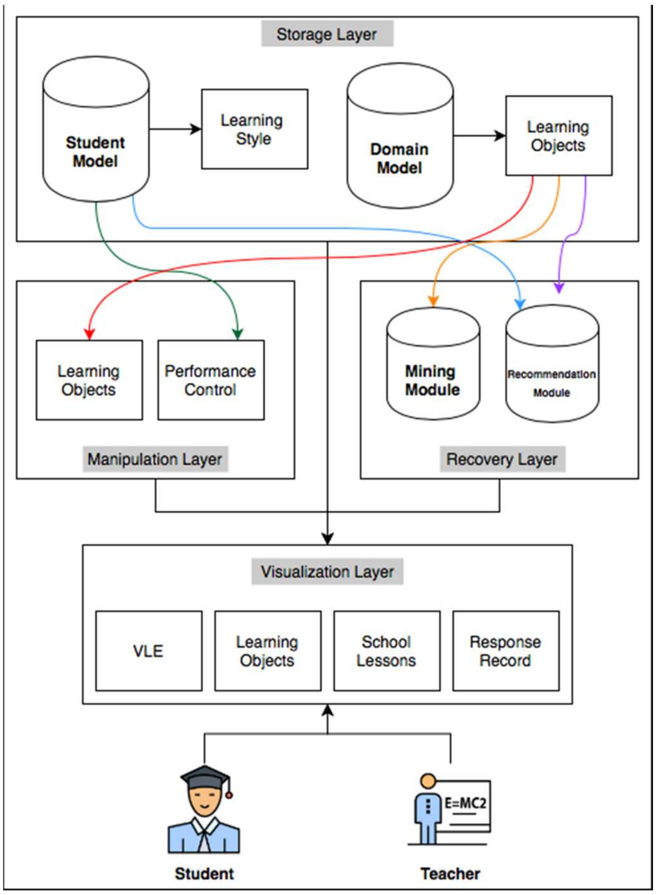

Fig. 4. Dynamic Model.

After the application of the questionnaire, the data will be organized in two stages: the first aims to define the profile of the students; the second aims to identify and insert students' preferences and demographic data, such as: name, enrollment, demographic data, format of the material presented, etc.

After building the student profile and identifying and entering preferences, the information should be inserted into a list of student information for each student's profile. The next step after defining student profiles and inserting facts is to build the rules structure that leads to the construction of recommendations.

Similarity measure with the recommendation approach based on a collaborative filter. It becomes necessary to include a dynamic model (shown in Figure 4) to add, based on previous activities, the accumulated evidence of the previous interaction for the same activity. After each activity is completed by a student, the results are used to decide the best way to guide him or her.

To recommend a learning object, the student's learning style will be considered, identifying the similarity between the student's profile (stored in the Student Model), and the description in the metadata of the learning objects (stored in the Domain Model). The association between these two pieces of information allows us to identify which resources should be recommended for students. The smaller the similarity, the less likely the learning object will be suitable for that student.

At the end of each recommendation, students will be asked to make an assessment to indicate the level of satisfaction with the suggested learning object. In addition, we intend to analyze data on user access (clickstream), focusing on the following attributes:

- Did the student access the recommended learning object?
- How long did it take to view the suggested feature?
- Did the suggested learning object help with the content of the course?

IV. Assessment Metrics

There are different metrics for assessing the accuracy of a recommendation system. These metrics are typically divided into two broad groups: Scoring Accuracy and Ranking Accuracy.

A. Scoring Accuracy

A recommendation system predicts the degree of satisfaction that the user would have for each item that has not yet been seen by the user. In the context of the dataset used in this work, the degree of satisfaction is the grade that the user explicitly gives to the item. Grade accuracy metrics assess the accuracy of these predicted grades, that is, the predicted grade is compared to the original grade so that the closeness between them is assessed.

This type of metric is in fact the most used in systems with explicit preferences. The two main metrics of grade accuracy are the mean absolute error (MAE) and the root-mean-square error (RMSE), which are calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|r_i - \tilde{r}_i| \tag{4.1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \tilde{r}_i)^2} \tag{4.2}$$

Where n is the total number of pairs (user, item) in the test dataset, $\tilde{r}_i$ is the i-th predicted grade and r_i is the corresponding true grade. The value of both metrics is always non-negative, and the smaller the value, the more accurate the system. The main difference between these two metrics is that the RMSE heavily penalizes scores that are very outliers because the differences are squared, unlike the MAE that uniformly penalizes the differences [21].

B. Ranking Accuracy

The function of the classification accuracy metrics is to assess the relevance of the recommended items. For this, it is necessary to know how to classify an item as relevant or not. For this reason, this type of metric is most commonly used in systems with Boolean or implicit notes, but it can also be used in systems with explicit notes using a note threshold (for example, an item it is considered relevant for a user if his grade is greater than 70). In this case, it is clear that the metric depends on the choice of this threshold.

Two widely used metrics are precision and recall. Precision assesses what fraction of the recommended items is actually relevant, while recall assesses what fraction of all relevant items was recommended. The accuracy *P(L)* and the recall *R(L)* referring to the list of recommended items *L* for user *u* are calculated as follows:

$$P(L) = \frac{relev_u(L)}{|L|} \tag{4.3}$$

$$R(L) = \frac{relev_u(L)}{|Relev_u|} \tag{4.4}$$

Where $relev_u(L)$ is the number of relevant items in the list of recommended items for user *u* and Relev*u* is the set of all items relevant for user *u*. The value of these metrics is always between 0 and 1, and the bigger, the closer to 1, the better.

In this work, the metric used was the RMSE. It was chosen for the following reason: most works in the literature that evaluate systems that use explicit preferences also use a precision metric of grades.

V. Conclusion and Future Work

The main objective of personalization is to provide personalized responses to certain user actions, in order to meet specific requirements, as well as to give meaning to information that is often not used intelligently in applications. In the context of teaching and learning, a benefit of personalization refers to the ability to propose an easy, intermediate or complex study sequence for a given student, according to their needs, their style and learning objectives.

Through the results organized in our recommendation model, we can see:

- The recommendation of content in a personalized way for each student according to their learning preferences.
- The identification of the learning style can assist in the recommendation of the contents, and the evaluation method provided by the professor of the discipline.
- Feedback on recommended learning objects can be tracked more accurately, in view of students' personal characteristics and learning preferences.
- Learning objects are recommended according to the information stored in the student's model, through the educational data mining.

As a contribution of this research, we present a recommendation model divided into four modules: the student model considers the students' learning style, in addition to personal and academic data stored in the VLE database. The domain model stores all course information, including learning objects. The mining module assists in the interpretation of student data, and the recommendation module is responsible for retrieving information from the mining module and assessing the capabilities to recommend appropriate resources for the student's profile.

This model is being programmed to work together with VLE Moodle, but it can be extended to other VLEs. As future work, we intend to present the application and evaluation of the recommendation model with classes of real students, and to analyze the results obtained.

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