An Adaptive Mechanism for Moodle Based on Automatic Detection of Learning Styles

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Abstract— This paper proposes an automatic approach that detects students' learning styles in order to provide adaptive courses in Moodle. This approach is based on students' responses to the ILS and the analysis of their interaction behavior within Moodle by applying a data mining technique. In conjunction to this, an adaptive mechanism that was implemented in Moodle is presented. This adaptive mechanism builds the user model based mainly on the proposed approach for automatic detection of learning styles in order to adapt the presentation and the proposed navigation to students' different learning styles and educational objectives. An evaluation study was conducted to evaluate the proposed approach for automatic detection of learning styles and the effect of the adaptive mechanism. Two groups of students were formed, namely the experimental and the control. The first had access to a Moodle course that automatically detected their learning styles and exploited the adaptive mechanism, whilst the second had access to the standard version of a Moodle course. The results were promising since they indicated that our proposed approach for automatic detection of learning styles attained adequate precision compared to other works, even though the patterns considered are less complex. Additionally, the results indicated that the adaptive mechanism positively affected students' motivation and performance.

Keywords—Adaptive and intelligent educational systems, distance learning, learning styles, learning management systems, personalized E-learning, user modeling

1 Introduction

Learning style refers to attitudes and behaviors which determine the way an individual learns something new (Honey and Mumford 1992). Gregorc (1979) defines learning styles as the characteristic sets of behavior that persist, although goals and content may change, that indicate how individuals learn. Students' learning styles are the differences in the methods used to acquire and process information (Alharbi et al. 2011). For instance, some students learn more effectively when information is presented as images, others prefer text and some prefer facts, while others prefer theoretical knowledge.

In the literature there are many references to the significance of learning styles and their impact on the learning process. Clearly, students benefit from material and approaches that suit their learning styles (Akbulut and Cardak 2012). Correspondingly, it has been shown that problems arise from a mismatch between teachers' expectations of the way students learn and students' preferred learning styles (Mills et al. 2005). A possible explanation for this might be that when their particular learning style is not included in the learning process, students are not motivated and lose interest (Felder, Felder and Dietz 2002).

The main purpose of using learning styles is to adapt the content presentation to the learner (Peter, Bacon and Dastbaz 2010), either within Adaptive Educational Hypermedia Systems (AEHS) or Learning Management Systems (LMS). However, more recently several approaches to the automatic detection of learning styles have been proposed, in contrast to the traditional way which has been through students' completion of a specific questionnaire.

To begin with, several AEHS have been proposed in order to provide learners with courses that suit their individual needs and characteristics, such as their learning styles (Peter, Bacon and Dastbaz 2010; Cabada, Estrada and García 2011; Bachari, Abelwahed and Adnani 2011; Latham, Crockett and McLean 2014; Popescu and Badica 2011). Thus, adaptivity, i.e., taking into consideration individual learning characteristics and needs is the main advantage of these systems. A major drawback is that they only support a few functions of web-enhanced education. On the other hand, LMS, offer various sets of tools to support teachers in creating, administering and managing online courses. However, LMS do not consider a student's learning style and deliver the same set of educational resources to all students. Recently, there has been growing interest in enhancing adaptivity in LMS. In order to exploit their benefits and combine them with those of AEHS, the use of adaptation techniques in LMS has been proposed (Graf, Kinshuk and Ives 2010; Despotović-Zrakić et al. 2012; Surjono 2014; Liyanage,

Gunawardena and Hirakawa 2014).

This article's contribution is reflected in a new flexible and generic approach for detecting learning styles and adapting a LMS course considering not only students' responses in a questionnaire but also their interaction with the system, in order to overcome the disadvantages of each approach. More specifically, the proposed approach applies a data mining algorithm to automatically detect students' learning styles and to adapt the presentation and proposed navigation through a Moodle course to students' learning styles and educational objectives. The benefit of the research is reflected in its wide applicability in Moodle-centric online learning systems. The proposed approach for automatic detection of learning styles has the advantage of being generic and applicable to any LMS as long as it is able to track students' interaction with the system.

To fulfill the requirements of the aforementioned system, four research questions were investigated.

RQ1: How can learning styles be automatically and accurately detected in Moodle?

RQ2: How can adaptive courses based on learner behavior and knowledge be provided in Moodle?

RQ3: Does an adaptive mechanism based on learner behavior and knowledge affect system usability and motivational appeal?

RQ4: Does an adaptive mechanism based on learner behavior and knowledge improve student performance more than the standard version of Moodle?

In addition to the RQ1 this study sought to examine whether the automatic detection of learning styles attains high precision.

The remainder of the paper is organized as follows: the next section (2) gives a short description of the approaches that have been used for the detection of learning styles. In sections 3 and 4, the proposed methodology and the evaluation study are presented, respectively. This is then followed by section 5 where the discussion section sets the results in relation to the research questions and addresses some limitations of our study, and lastly, in the final section (6) are the conclusions.

2 Related Work

2.1 Felder-Silverman Learning Style Model

There are a wide variety of theories and learning style models that have been put forward. Coffield et al. (2004) mentioned that 71 different theories exist, 13 of which are characterized as major models with respect to their importance, their convection, their influence on other models and the existence of assessment instruments. Sampson and Karagiannidis (2002) mentioned 11 main learning style models and the respective assessment tools.

The Felder-Silverman Learning Style Model (FSLSM) (Felder and Silverman 1988) is used far more often than any other in AEHS, mainly because it offers an in-depth description of learning styles (Carver, Howard and Lane 1999). There are four dimensions each with two scales: active/reflective, sensing/intuitive, verbal/visual and sequential/global, which are related to the way students process, perceive, receive and understand information. The resulting preferences are considered as tendencies, since even those learners with a strong preference for a particular learning style can at times act differently (Graf 2007).

The Index of Learning Styles (ILS) was developed in order to assess FSLSM (Felder and Soloman 1997). ILS is a 44-item questionnaire with 11 forced-choice questions about each of the four dimensions. Each answer option (a or b) corresponds to one or the other category of the respective dimension (e.g., active or reflective). For statistical analyses it is convenient to use a scoring method that counts "a" responses, so that a score of a dimension would be an integer ranging from 0 to 11. Using the active/reflective dimension as an example, zero or one "a" responses would represent a strong preference for reflective learning, while ten or eleven such responses means there is a strong preference for active learning. Every learner, therefore, has a personal preference for each of the four dimensions and his/her learning style in total is expressed with four values ranging between 0 and 11.

2.2 Detection of Learning Styles

There are two main ways of detecting learning styles, namely collaborative and automatic detection approaches. The first one asks students to fill out a special questionnaire which refers to the selected learning style model. Approaches that are solely based on the use of such questionnaires were (Surjono 2014; Yang, Hwang and Yang 2013). Even though these questionnaires constitute reliable and valid instruments for identifying learning styles (Felder and Spurlin 2005), they have been subjected to some criticism over the last years (Viola et al. 2007). To begin with, the learner has to respond to many questions; a procedure, which apart from having little meaning can be frustrating as well. There is also a high possibility that the learner's answers are arbitrary, which could mean that the obtained results are inaccurate and might not reflect the actual learning style. Moreover, questionnaires constitute a static

approach where the user model is initialized only once, usually at the beginning. Thus, any misclassification of a student's learning style cannot be revised.

In order to surmount these disadvantages, several approaches for the automatic detection of learning styles have been proposed. These approaches are based on the analysis of behavior data that are gathered from the students' interaction with the system, such as his/her actions and their duration. Thus, no additional effort is required by the students, such as answering a questionnaire. Consequently, they can focus on learning rather than providing feedback about their learning preferences. Furthermore, an automatic detection approach has a greater potential to be error-free as real data is used in order to detect students' learning styles (Feldman, Monteserin and Amandi 2015). Finally, better results can be achieved with these approaches because, rather than giving learners' specific state at the start, it describes their current state.

Automatic detection techniques can be divided into two subcategories: data-driven and literature-based (Graf 2007). The first approach aims at building a classifier that imitates the questionnaire mentioned above, yet free from the respective disadvantages. In order to build a classifier, different data mining algorithms have been used, such as decision trees (Cha et al. 2006; Crockett, Latham and Whitton 2016; Özpolat and Akar 2009), Bayesian networks (Graf 2007; García et al. 2007, Alkhuraiji, Cheetham and Bamasak 2011), neural networks (Kolekar, Sanjeevi and Bormane 2010; Zatarain-Cabada et al. 2010), hidden Markov models (Cha et al. 2006), and genetic algorithms (Yannibelli, Godoy and Amandi 2006). Liyanage, Gunawardena and Hirakawa (2016) compared the performance of four different data mining algorithms, including J48, Bayesian network, naïve Bayes, and random forests. The specific study revealed that the J48 algorithm was the most suitable for their system and dataset. All these algorithms take data gathered from student's interactions with the system as input and return their learning preferences in terms of the adopted learning style model. However, since these approaches strictly depend on the available data, a representative dataset is essential to build an accurate classifier (Dung and Florea 2012). Besides the above mentioned classification algorithms, clustering approaches have also been proposed (Despotović-Zrakić et al. 2012; Klasnja-Milicevic et al. 2011). The major disadvantage of these approaches is that since they do not allow real time adaptation, teachers are required to monitor students' progress and if needed move them to another cluster manually.

The literature-based approach uses students' behavior to obtain hints about their learning style and then applies a simple rule-based method to calculate the learning style from the number of matching hints. This approach is similar to the method used for calculating learning styles in ILS and has the advantage of being generic and applicable for data (Graf 2007). However, the literature-based approach may not be efficient in estimating the importance of the different hints used for calculating the learning styles. Several automatic detection approaches have been proposed (Popescu and Badica 2011; Liyanage, Gunawardena and Hirakawa 2014; Graf 2007; Dung and Florea 2012; Atman, Inceoğlu and Aslan 2009; Şimşek et al. 2010). Although the precision attained in these approaches was promising, at this point it should be pointed out that some of them used relatively small samples and therefore, their validity can be challenged. For example, in (Liyanage, Gunawardena and Hirakawa 2014; Atman, Inceoğlu and Aslan 2009; Şimşek et al. 2010) there were only 17, 22 and 27 students, respectively who participated in the studies.

There are differing views in the literature when comparing the two automatic detection subcategories. Despite the promising results of the literature-based approaches (Graf 2007; Dung and Florea 2012) they require some knowledge of psychology and cognitive science to correctly estimate the importance of the hints (Feldman, Monteserin and Amandi 2015). On the other hand, computer science researchers are more familiar with data-driven approaches, because they require the use of an artificial intelligence classification algorithm to automatically detect learning style preferences (Feldman, Monteserin and Amandi 2015).

3 Methodology

3.1 Introduction

In order to investigate RQ1 and RQ2, we designed and implemented in Moodle an approach for the automatic detection of learning styles and an adaptive mechanism providing courses that suit students' learning preferences as these are expressed by their learning styles and educational objectives respectively. The architecture of the proposed system is illustrated in Fig.1. The user model can be built with techniques based either on learner knowledge or on user behavior (Kobsa, Koenemann and Pohl 2001). However, "hybrid" approaches can also be found in the literature (Kazanidis and Satratzemi 2009). This term is used because the user model in such systems is built with techniques that are based on both learner knowledge and behavior. Nevertheless, such systems are not dynamic as regards either

of the dimensions mentioned above. In addition, learning style detection can be achieved with the use of special questionnaires or automatic approaches. Our system is innovative as it is "hybrid" regarding both static and dynamic student modeling modules, while at the same time exploiting the automatic detection of learning styles and the ILS questionnaire in order to attain more accurate results.

When designing the proposed system's architecture, our main concern was the implementation of a generic and flexible system that would remain unaffected by Moodle updates. This was achieved by implementing all functionality through the development of independent php extensions in Moodle rather than modifications to the Moodle core. Five extensions were developed so as to integrate the proposed framework into Moodle. The first two deal with storing learning styles and students' educational objectives, respectively. The third enables the teacher to provide the required metadata for the learning objects, while the fourth implements the automatic detection of learning styles. The fifth extension enables the system to automatically provide courses that suit students' learning preferences as these are expressed by their learning styles and educational objectives.

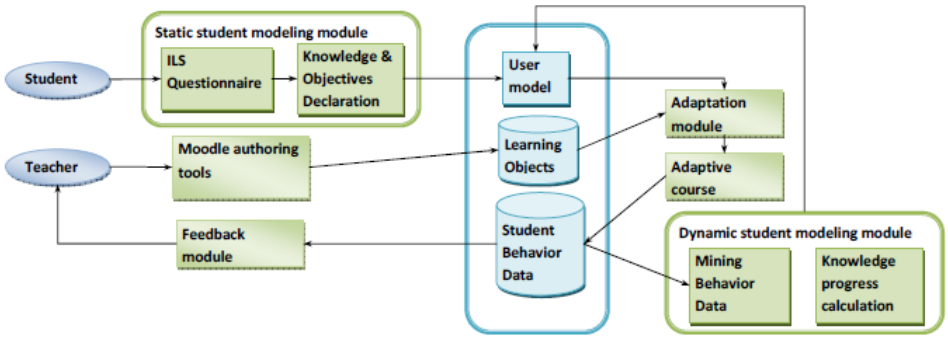

Fig. 1 Architecture of the proposed system

3.2 Detection of Learning Styles within Moodle

Learning style detection can be achieved either with collaborative or automatic approaches (Brusilovsky 1996). Collaborative user modeling requires that the user actively engage in the modeling process so that the necessary data is collected (Brusilovsky 1996). In our case, such information can be received from the completion of the ILS questionnaire.

While collaborative learning style detection requires students to provide feedback regarding their learning preferences, automatic learning style detection is based on the concept of looking at what students are actually doing in a course. Learning styles can be obtained from the analysis of their interactions with the system.

3.2.1 Collaborative learning style detection - ILS Questionnaire

In the present system we decided to adopt FSLSM to represent students' learning style preferences. In order to obtain this information, ILS was used for collaborative user modeling. Therefore, students were asked to answer ILS right after their first login. The user model is then built, as long as the specific responses are provided. Although it was decided to base the detection of users' learning styles mainly on an automatic detection approach, the use of ILS was also adopted because this way, the system can adapt the course to each student's learning preferences from the very beginning. The disadvantages of using only ILS have been referred to previously.

3.2.2 Automatic learning style detection - Mining Behavior Data

Up until now, conforming to the data-driven approach, all systems that have been used for the automatic detection of learning styles have implemented one specific data mining algorithm. This means that should a researcher wish to apply a different algorithm in the system, it would have to be implemented from scratch. Another part to our technical innovation, which was for the sake of achieving flexibility, is that we decided to run Weka (Weka, 2014) online. Weka is open source software that consists of a collection of machine learning algorithms for data mining tasks. It contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. The algorithms can either be applied directly to a dataset or called from Java code. The direct application of the algorithms to a dataset can be implemented either via the graphical interface or the command line. The latter option is adopted in our case.

To investigate RQ1, an extension was implemented in Moodle to enable communication with Weka, which should, in turn, be installed on the server. The extension stores the command that has to be

executed in Weka in a string variable. Next, the respective command is executed by passing this string as input to "system" function. Figure 2 depicts the interface between Moodle and Weka to automatically detect students' learning styles in order to achieve dynamic user modeling.

Weka has also been used by other researchers (Liyanage, Gunawardena and Hirakawa 2016) in a different way. They implemented the data mining algorithm by developing Java code that ran on the server once a day. Our proposed architecture has two substantial advantages though. The first is that it is easily implemented by running WEKA online but in the background, without producing overload as this functionality is not used that often and then only by the teacher. The second and most important is that by changing only the respective command line which stores the Weka command in the string variable, the entire algorithm can be replaced by another. Thus, flexibility can be achieved and the advantages of a very powerful tool such as Weka can be exploited not only for the implementation of the algorithm but also for data pre-processing. The steps of the proposed automatic detection of learning styles are depicted in Fig. 3.

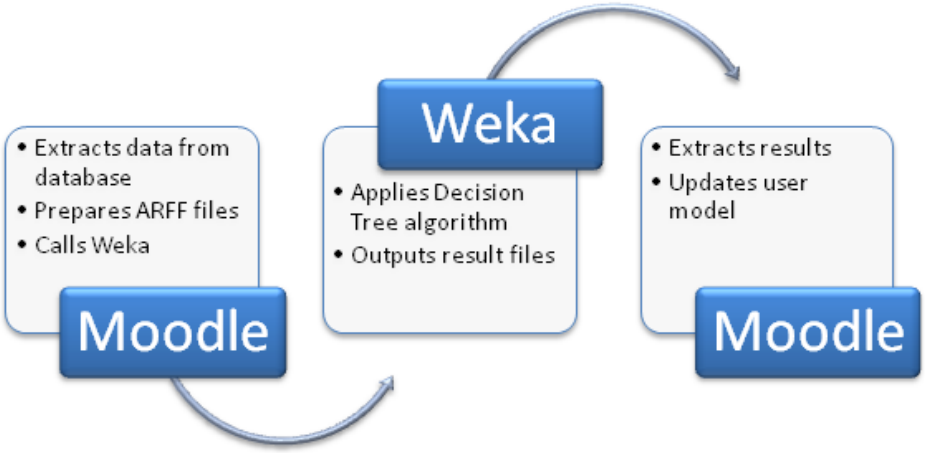

Fig. 2 Interface between Moodle-Weka to automatically detect students' learning styles

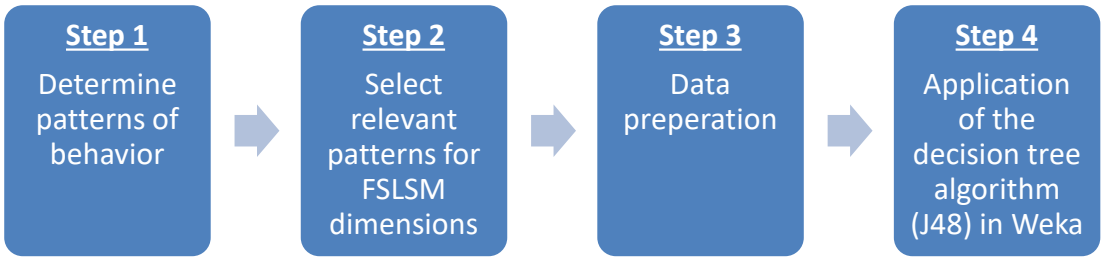

Fig. 3 Steps of the proposed approach for automatic detection of learning styles

The first step of the proposed approach for automatic detection of learning styles is to determine the required learner behavior relevant for the detection process. In addition, the proposed approach should be generic so as to be applicable to different LMS. Thus, the selection of the incorporated learning objects and behavioral patterns not only need to be relevant for detecting learning styles based on FSLSM, but also LMS should be able to gather such information. This last requirement entails that LMS should include the selected types of learning objects and they should be able to track information relevant to selected patterns. Moreover, in order to provide adaptive courses to students, the type of learning objects that will be used should match diversity of learning styles.

It was, therefore, decided to use seven different types of learning objects: outlines, content objects, videos, solved exercises, quizzes, open-ended questions, and conclusions. Outlines are used to present an overview of the educational objectives of the current section. Content objects present the theory of the section. Videos explain basic concepts of theory and provide hints for problem solving. Solved exercises consist of the description of an exercise and its solution. Quizzes include multiple close-ended questions, while the open-ended questions require learners to provide a solution and their reasoning for it. Finally, conclusions summarize the main points of the current section's theory.

Content objects, outlines, conclusions and videos are not distinguished by Moodle since they are all created as resources. In order to apply the adaptation algorithm which is described in the following subsection, the teacher must annotate them with metadata during their creation. To achieve this, we implemented an extension to Moodle authoring tools which enables one to state the specific type of resource.

The behavioral patterns that we decided should be used are related to the total time that a student studies a specific type of learning object and the number of visits to it. Thus, two values for each of the seven types of selected learning objects were used. However, relative values were preferred to absolute ones because they are more meaningful as they express students' actions in terms of the total amount of their effort. In order to calculate the relative values, the absolute values of time and number of visits were divided by the total time spent on the course and the total number of visits. Moreover, patterns related to the review of the quizzes were also used. The total set of behavioral patterns that were decided to be used is presented in Table 1.

Table 1 Patterns of behavior

Pattern	Description
outline_dur	relative time spent on outlines
outline_vis	relative number of visits on outlines
content_dur	relative time spent on content objects
content_vis	relative number of visits on content objects
video_dur	relative time spent on videos
video_vis	relative number of visits on videos
conclusion_dur	relative time spent on conclusions
conclusion_vis	relative number of visits on conclusions
solved_dur	relative time spent on solved exercises
solved_vis	relative number of visits on solved exercises
quiz_dur	relative time spent on quizzes
quiz_vis	relative number of visits on quizzes
quiz_review_dur	relative time spent on reviewing quizzes' results and feedback
quiz_review_vis	relative number of visits on reviewing quizzes' results and feedback
open_dur	relative time spent on open-ended questions
open_vis	relative number of visits on open-ended questions

The relevant patterns for FSLSM dimensions are selected in the second step of the proposed approach for automatic detection of learning styles. The literature regarding FSLSM (Felder and Silverman 1988) describes the expected learners' behavior for all learning style dimensions and, consequently, provides a framework to find the relevant patterns for each dimension. Based on the FSLSM we constructed Table 2 in order to depict the preferred learning object for each learning style. The specific analysis had also been used by other researchers in related works (Graf 2007; Atman, Inceoğlu and Aslan 2009; Graf, Kinshuk and Liu 2009; Karagiannis and Satratzemi 2017).

Table 2 Preferred learning object for each learning style

	Outline	Content	Videos	Solved exercises	Quiz	Open-ended questions	Conclusion
Active					+	+	
Reflective	+	+	+	+			+
Sensive			+	+	+	+	
Intuitive		+				+	
Visual			+				
Verbal		+				+	
Sequential			+	+			
Global	+		+	+			+

Table 3 summarizes the relevant patterns for each learning style dimension of FSLSM. The "+" and

"-" indicate a high and low occurrence from the viewpoint of an active/reflective, sensing/intuitive, visual/verbal, and sequential/global learning style. Being polar opposites means that when there is a high occurrence of a specific behavior giving an indication for one pole, there is a low occurrence of the same pattern hinting at the detection of the opposite pole.

Table 3 Relevant patterns for each dimension of FSLSM

Active / Reflective	Sensing/ Intuitive	Visual/ Verbal	Sequential/ Global
content_dur (-)	content_dur (-)	content_dur (-)	outline_dur(-)
content_vis(-)	content_vis(-)	content_vis(-)	outline_vis (-)
outline_dur(-)	solved_dur (+)	video_dur (+)	conclusion_dur (-)
outline_vis (-)	solved_vis (+)	video_vis (+)	conclusion_vis (-)
solved_dur(-)	quiz_dur (+)	open_dur (-)	solved_dur (+)
solved_vis (-)	quiz_vis (+)	open_vis (-)	solved_vis (+)
video_vis (-)	open_dur (+)		
quiz_dur (+)	open_vis (+)		
quiz_vis (+)			
quiz_review_ dur (-)			
quiz_review_ vis (-)			
open_dur (+)			
open_vis (+)			
conclusion_dur (-)			
conclusion_vis (-)			

The third step of the proposed approach for automatic detection of learning styles prepares the data that are going to be used as input in the decision tree algorithm. Moodle, as well as most LMS, stores log information in an event-based way. That means that once a student requests a specific learning object or performs any other action in the system, a new entry is made in the log table (mdl_log Moodle's table) of the system's database. For the data to be used as input in a decision tree algorithm, they have to first be transformed into raw data, meaning that a new table has to be created comprising a different row for each student. A new table was created in Moodle's database as we did not want to modify mdl_log being a core Moodle table. Furthermore, this new table was necessary as the relevant data needed to be appropriately transformed and could not be extracted from Moodle and used simultaneously. In turn, each row of the new table should consist of cumulated information extracted from the mdl_log table regarding each one of the patterns that are presented in Table 1. Additionally, each row has to store information about the student's learning style for each dimension as detected from answering ILS. Thus, a new table is created in Moodle's database consisting of the above mentioned information. After the transformation of data from absolute to relative values, relevant patterns for each dimension have to be considered. Therefore, it was decided to create four different csv files from the specific table; one for each dimension of FSLSM. Each one of these csv files is created by extracting from the table only the patterns that are relevant for the specific dimension, as well as the equivalent learning style preference.

Finally, prior to applying the decision tree algorithm, each csv file is randomly divided into a train and test dataset. In order to better model the underlying distribution, 70-80% of the dataset is commonly used for training and the remaining 20-30% for testing. We, thus, decided that from the initial dataset, the training and testing would be 80% and 20%, respectively.

The fourth step towards detecting students' learning styles is the application of the decision tree algorithm in Weka. The algorithm that is adopted is J48 which builds a decision tree from a set of training data, using the concept of information entropy. Four different trees were created, one for each dimension of FSLSM. After running the J48 algorithm, the respective predictions for all the students are stored in four new csv files, one for each dimension of the FSLSM. A new table in Moodle's database was created in order to update the user model with these results.

3.3 Adaptive Course

Once the automatic detection of learning styles has occurred, Moodle is ready to provide an adaptive course based both on the collaborative and automatic user modeling approaches. To answer

RQ2, an adaptive mechanism was designed both regarding learner behavior and knowledge. This mechanism is presented in the following subsections.

3.3.1 Adaptivity Regarding Learner Behavior

In order to adapt the course to the students' different learning preferences in a flexible way, it was decided to use a sufficiently flexible mechanism (Graf, Kinshuk and Ives 2010), which was modified to correspond to our needs. It was decided, therefore, that the course would consist of sections, each with a different theoretical concept, and its own learning objects. Fig. 4 illustrates a screenshot of a course section in Moodle. Each section's learning objects were created based on the concepts that were taught in the respective lecture. Consequently, it can be assumed that it is valid to use them to evaluate whether students have known the content. Undoubtedly, the greater the variety of types of learning objects used, the better suited to students' different learning styles the course would be. However, due to the flexibility of the proposed mechanism, only one content object is required. The only type of learning object in the structure of our Moodle course that has a fixed position is the outline, which is the first one presented. Also, the conclusion is usually the last learning object presented in each section for all learner types, with the exception of global learners. Each section structure is designed to consist of two different areas, which we called the "area before content" and the "area after content". The "area before content" is positioned immediately after the outline and prior to the content objects and whose aim is to stimulate the learner to become actively involved in this section. It includes one of the available learning objects. This is then followed by the content objects, of which we decided to use smaller rather than bigger ones in order to provide the flexibility to learners to find what they are looking for more easily. Immediately after the content objects, there is the "area after content". This specific area includes all the remaining learning objects of the current section, arranged in descending order in accordance with the algorithm that is presented in the following paragraphs.

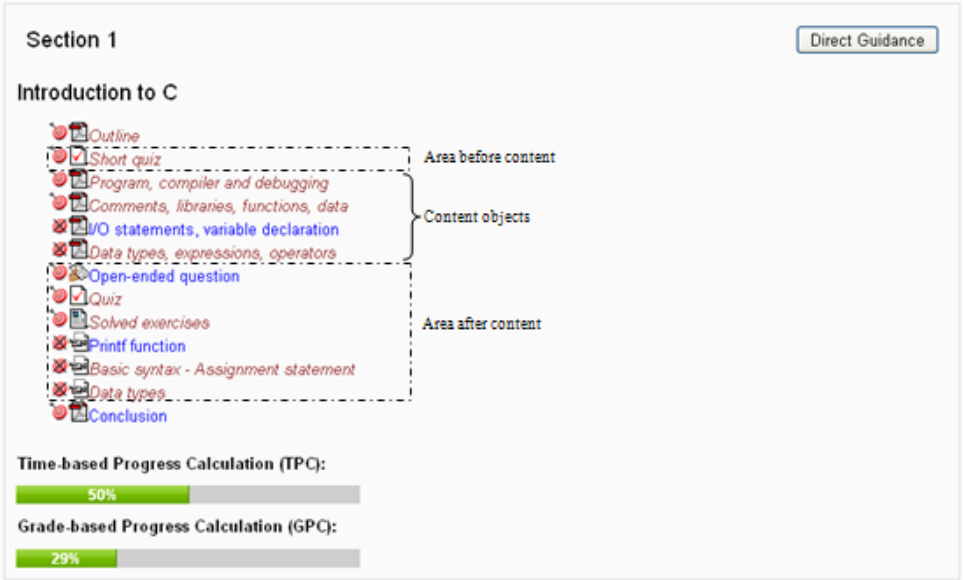

Fig. 4 Screenshot of a course section in Moodle

The adaptation features show how a course differs among learners with different learning styles (Graf, Kinshuk and Ives 2010; Graf 2007). The available literature (Felder and Silverman 1988) should be considered in order to select the appropriate features, the types of learning objects and the course structure. In our model, the adaptation features deal only with the position of the learning objects in the particular section. Table 4 presents the learning objects preferred by each different learning style for both areas, indicating, therefore, what features are appropriate for each style.

Table 4 Preferred learning object for each learning style

	Area before content		Area after content
Active	Short quiz, Open-ended questions	Content	Quiz, Open-ended questions
Reflective			Solved exercises, Videos
Sensing	Open-ended questions, Videos		Solved exercises, Quiz, Videos,

			Open-ended questions
Intuitive	Short quiz, Open-ended questions		Open-ended questions
Visual	Videos		Videos
Verbal	Solved exercises		Open-ended questions
Sequential			Solved exercises, Videos
Global	Solved exercises		Solved exercises, Videos

The set of the selected features for both areas are presented in Table 5. Two additional features were also included. The first concerns the appearance of outlines not only at the beginning of a section but also between the content objects. The second feature is the conclusion appearing either right after the content objects or at the end of the section. These specific features are very important for global learners as this type are interested in getting an overview of the course. They have no particular effect though on the other learning styles.

Table 5 Adaptation matrix

	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Short_quiz_before	1	-1	-1	1	0	0	-1	0
Solved_before	-1	-1	-1	-1	0	1	-1	1
Question_before	0	-1	1	1	0	0	-1	0
Video_before	-1	-1	1	-1	1	-1	-1	0
Outline	0	1	0	0	0	0	0	1
Conclusion	0	1	0	0	0	0	0	1
Solved_after	-1	1	1	-1	0	0	1	1
Quiz_after	1	-1	1	0	0	0	0	-1
Video_after	-1	1	1	-1	1	-1	1	1
Question_after	1	0	1	1	-1	1	0	-1

The next step towards providing adaptivity regarding learner behavior is the application of the algorithm that will be used to adapt the proposed navigation through a Moodle course to students' learning styles. A well-established methodology found in (Graf 2007) was adopted and the adaptation matrix was modified to suit our study needs. Thus, a matrix is built consisting of 10 rows –one for each of the selected adaptation features- and 8 columns -one for each of the different values of each dimension of FSLSM. The matrix cells are filled in as follows: 1 if the adaptation feature supports the specific learning style, -1 if the feature should be avoided in order to support the specific learning style, and 0 if the feature has no effect on the learning style according to the literature (Felder and Silverman 1988).

This adaptation matrix is accessible from Moodle via a special form that we created, to enhance flexibility to the proposed mechanism. The default values (Table 5) of the matrix cells can, therefore, be modified by the teacher. By extension, in the case where they decided to use the learning objects differently, they can modify the effect that the adaptation features has on each learning style.

Based on the actual learning styles of the students, as obtained from the ILS questionnaire, Graf added up the respective values for each adaptation feature, additionally using the strength of the learning style preference as a weight (Graf 2007). In our approach, we did not included the strength factor, however, we did consider the learning styles as derived from both the ILS questionnaire (LS_{ILS}) and those derived from mining the behavior data with the decision tree algorithm (LS_{AD}). More specifically, the respective values of the adaptation matrix are added up for each of the adaptation features, firstly in terms of LS_{ILS} followed by LS_{AD}, and finding the average of the two which makes up the final ranking score. At this point, it should be mentioned that, although the results of the decision tree algorithm (LS_{AD}) are trained based on the ILS responses (LS_{ILS}), it was decided to use both of them. In so doing we were thus able to overcome the disadvantages of using only ILS and to eliminate any probable outlier values. More specifically, the possibility for the ILS responses to be inaccurate has been referred to previously. By dividing the initial dataset to training and testing one we further reduce the possibility that inaccurate responses are used as training data. This way the attained precision of the

detection algorithm is improved.

In order to exemplify the calculation of the final ranking score method, let us take the case of a student whose learning style is active, sensing, visual and sequential according to the ILS questionnaire (LS_{ILS}), and active, intuitive, visual and sequential according to the decision tree algorithm (LS_{AD}). Taking the first adaptation feature concerning the "area before content" namely the "short_quiz_before" feature (Table 5), we have to add up the respective values of the adaptation matrix, firstly for LS_{ILS} and then for LS_{AD}. Therefore, the ranking score for the specific feature for the LS_{ILS} is 1-1+0-1, which results in -1. Similarly, the ranking score for the LS_{AD} is 1+1+0-1 which results in 1. The final ranking score for the "short_quiz_before" feature is equal to the average of these two values i.e., it is equal to 0. It should be pointed out that our method does not consider which of the learning style preferences is stronger but they all contribute equally to the calculation of the ranking score.

In accordance with the learning style literature (Felder and Silverman 1988) each dimension of FSLSM can be supported in a number of ways based on the proposed mechanism. Taking the example of active learners, it should be mentioned that, due to their preference for doing something active with the information, quizzes and open-ended questions are recommended for them. In order to stimulate students' interest in the subject matter of the section, it is proposed that these learning objects be presented in "area before content". Therefore, the respective matrix cells are filled in with 1 (Table 5). In contrast, solved exercises and videos are not suitable to this learning style and should definitely not be included in the "area before content" but rather towards the end of the "area after content". The outline and conclusion do not appear to have much effect on active learners, these features being more suited to reflective and global learners, thus the respective cells are filled in with 0. The matrix cells (Table 5) regarding the other dimensions of FSLSM, are similarly filled in.

Regarding the adaptive techniques, it was decided to use adaptive sorting (Brusilovsky 2001). Firstly, the ranking scores for all the adaptive features that were to be used were calculated. This was followed by the composition of the Moodle course, in consideration with the general structure described here. In the "area before content", only one type of learning object is presented, with the intention of stimulating learners' active involvement, and at the same time avoiding a high cognitive load before students have become familiar with the content objects. The "area before content", therefore consists of the learning object with the highest ranking score out of the solved exercises, videos, open-ended questions, and short quizzes. In the case where more than one learning object has equal ranking scores, all are presented in this section. As regards the "area after content", all learning objects are ranked in descending order according to their score, which determines their positioning within the specific area. In addition to adaptive sorting, a direct guidance button was embedded in each section. This button is helpful mainly to learners who have a low level of e-learning experience.

3.3.2 Adaptivity Regarding Learner Knowledge

As described at the beginning of section 3, the proposed hybrid user model is built with techniques based both on learner knowledge and behavior. Consequently, adaptivity is provided for both aspects. As regards adaptivity based on learner knowledge, adaptive presentation and adaptive annotation (Brusilovsky 2001) are used.

The overlay model (Beck, Stern and Haugsjaa 1996) was used in order to represent the progress learners made in their knowledge. In this model, a student's knowledge is considered to be a subset of the expert's knowledge (Beck, Stern and Haugsjaa 1996). Throughout the learning experience, students acquire knowledge expecting to reach the same level as that of the experts without being able to learn anything more or different to him/her (Kazanidis and Satratzemi 2009). Learners' knowledge progress was calculated with the use of two different measures: the Time-based Progress Calculation (TPC) and the Grade-based Progress Calculation (GPC).

As regards the Time-based Progress Calculation (TPC) Moodle's authoring tool was expanded, which enabled it -apart from open-ended questions- to store for each type of learning object two different time values, namely t_min and t_max. In addition, another value, named w_i, is stored for each type of learning object, including open-ended questions. The minimum time required for a learner to study the specific learning object in order for it to be considered as "known" is represented by the t_min value, whereas the maximum time that a learner can study it is represented by the t_max value. Time values beyond this range signify that Moodle is probably in an idle state while the learner is doing something other than actually studying that particular learning object. If a time value exceeds the t_max limit, that particular value will not be taken into consideration and the respective learning object will be considered as "unknown". Time values below t_min are stored for each learning object. If their sum is beyond t_min value then the learning object will be considered as "known". In order to define t_min and t_max values for each learning object, a pilot study with a small sample of students was conducted. The students were equally distributed regarding their performance. The two values

previously mentioned, were calculated as the average of the times that all students spent on them.

As regards time progress, open-ended questions are considered as "known" if a solution is submitted, regardless of the time that the learner spent on them and the solution's correctness. Such a consideration is justified on the basis that TPC calculation is strictly made in relation to the students' efforts. The correctness of a solution which is expressed by its grade is considered in GPC calculation. The w_i value indicates the weight of importance of the specific learning object ranging from 0 to 1. The sum of w_i values for all the learning objects of a section equals 1. Having defined the above values, the TPC of a section is defined as follows:

$$TPC = \frac{1}{N} \sum_{i=1}^{N} f(t_i) \times w_i \qquad (1)$$

N stands for the quantity of learning objects of the specific section, w_i is the weight of importance of the i-th learning object, and function f is defined as the following:

$$f(t) = \begin{cases} 0, & t<t\_min \text{ or } t>t\_max \\ 1, & t\_min \leq t \leq t\_max \end{cases} \qquad (2)$$

The GPC measure of a learner's progress refers to his/her grades on Moodle activities that can be graded. Of the different types of learning objects selected for the course, only quizzes and open-ended questions are graded. The results of the short quiz do not contribute to the final assessment, since it is presented before the student has studied the theory, and the aim of this section is mainly to prompt active student participation. Each section includes one quiz and one open-ended question. Due to possible different specifications of a course, it was decided that these grades would have adjustable weights in the GPC. Therefore, the GPC is the weighted average of these grades. In our case, due to the fact that the quiz consists of several items and, is thus, more demanding than the open-ended question, it was decided that the weights would be 70% and 30% for quizzes and open-ended questions respectively. Therefore, the GPC of a section is defined as follows:

$$GPC = 0.7 \times grade_{quiz} + 0.3 \times grade_{open-ended} \qquad (3)$$

In sum, a section's TPC measures how much of the learning material is considered known in relation to the length of time spent by the student attempting it, whilst GPC measures the student's performance in the specific section. We believe that a combination of the two constitutes an adequate way to estimate a learner's progress on a specific section since both the student's effort and grades are taken into account. TPC and GPC are depicted in each section of the course with the help of two independent progress bars.

In conjunction to the above mechanism, the links of the learning objects considered as having been learnt are annotated differently. Specifically, a "known" learning object is annotated in italics in red, rather than upright letters in blue used for an "unknown" learning object. Finally, learners are asked to state their learning objectives for the course at the beginning. According to their statements, a respective icon appears before the learning object link, illustrating whether it constitutes an objective or not.

4 Evaluation Study

4.1 Introduction and Objectives

An evaluation study was conducted during the winter semester of the 2015/16 academic year in the context of the Procedural Programming introductory course taught in our department. Three research questions have to be investigated, given that RQ2 is investigated in subsection 3.3. Moreover, RQ1 is partially investigated in subsection 3.2.2 in which the proposed approach for automatic detection of learning styles is described. Therefore, the accuracy of the automatic detection of learning styles regarding RQ1 has to be investigated, which means that this study sought to examine whether the automatic detection of learning styles attains high precision. Consequently, this study objective was primarily guided by the following questions.

RQ1A: Does the proposed approach for automatic detection of learning styles attain high precision?

RQ3. Does an adaptive mechanism based on learner behavior and knowledge affect system usability and motivational appeal?

RQ4. Does an adaptive mechanism based on learner behavior and knowledge improve student performance more than the standard version of Moodle?

Regarding student performance, it was additionally investigated whether a relation between students' outcomes, their learning styles and the functionality of the recommended navigation sequence exist.

4.2 Participants

Two groups were formed, the experimental and the control to answer RQ3 and RQ4. Having been

informed about the existence of differences between each group, without knowing which is the experimental one though, students were assigned to a group based on their student number. It should be pointed out that all students succeeded in passing the university entrance exams with similar grades for Computer Science Studies, which was their first choice, confirming that they have comparable academic profiles. Nevertheless, as the two groups had been randomly formed, the possibility cannot be ruled out that those groups may have different skills and previous knowledge level. In order to refute this assumption, we investigated the two groups' average grades for another similar course that is also taught in the first semester in our department, namely "Algorithms in C". There was a slight but not statistically significant difference between the average grades of the experimental group with a mean score of 5.94 (SD = 2.417), and the control group with a mean score of 5.73 (SD = 2.604). It can thus, be assumed that the two groups were probably engaged to an equal degree in their studies and any differences in the study results might have been due to the proposed mechanism. Overall, 139 students participated in the study and also took the mid-term exam. They were almost equally assigned to each group. Thus, experimental and control groups consisted of seventy and sixty-nine students respectively. The distribution of students in each learning style as derived from the ILS questionnaire is presented in Table 6.

Table 6 Distribution of students in each learning style as derived from the ILS questionnaire

Group	Active/ Reflective	Sensing/ Intuitive	Visual/ Verbal	Sequential/ Global
Experimental	37/33	39/31	40/30	36/34
Control	34/35	38/31	37/32	33/36

4.3 Instruments

An evaluation questionnaire and TPC values stored in Moodle's database were used to answer RQ3. The evaluation questionnaire was divided into two main subcategories: system usability and motivational appeal, where students were asked to respond to six and five questions, respectively, providing feedback to investigate RQ3. The questionnaire consisted of five-point Likert type questions, ranging from 1 'strongly disagree' to 5 'strongly agree'. The questionnaire was based on similar works (Kazanidis and Satratzemi 2009; Popescu and Badica 2011; Despotovic et al. 2012). Cronbach's alpha was calculated to check the questionnaire's validity.

In order to answer RQ1a, there was a third subcategory in the questionnaire that only the experimental group had to respond to. More specifically, although ILS is proven to be a reliable and valid instrument (Felder and Spurlin 2005), misclassifications may occur which are due mainly to students' inaccurate responses to the questionnaire. In order to check this initial assumption, we included four relevant questions in the evaluation questionnaire, each of which describes a different dimension of the FSLSM. Each question thoroughly and in simple terms describes the behavior and preferences of each of the two learning styles of the specific dimension. Subsequently, students were asked to choose which of the two respective styles best suits them. For example, as regards the first dimension, they are asked whether they believe they are active or reflective learners. In addition, ILS questionnaire and behavior data that are gathered from the students' interaction with the system, such as his/her actions and their duration were also used to answer RQ1a.

The efficiency of the proposed mechanism was examined using student performance on the mid-term exam to answer RQ4. Similar approaches have also been used by other researchers in related works (Graf 2007). In addition, TPC and GPC values, stored in Moodle's database, were also used to answer RQ4.

4.4 Procedure

The Procedural Programming course is a 13-week long course consisting of a 2-hour weekly lecture and a 2-hour weekly laboratory. The students are required to take a mid-term exam worth 30% of their final grade. The study was conducted over the first six weeks of the course, up to the mid-term exam. During this time, students were presented with five sections on fundamental concepts of procedural programming, namely an introduction (I/O statements, data types, assignment statement), if statements, loops, functions and arrays. Both groups attended the same lectures and laboratories whilst using two different courses in Moodle for studying. The learning material was the same for the two courses. Each section consisted of an outline, content objects, videos, solved examples, one quiz, one open-ended question, and a conclusion. The experimental group were assigned the adaptive course described in Section 3 (Fig. 3), whereas, the control group were set the course which applied the standard version of

Moodle. Both collaborative and automatic detection of learning styles were only applied to the experimental group in order to build the user model and provide them with the adaptive course. Consequently, the results and the analysis regarding learning style detection are relevant only for the experimental group. On completion of the 5 sections of the respective Moodle course but prior to the mid-term exam, both groups of students had to answer the questionnaire to evaluate the attended course.

4.5 Measures

In order to investigate RQ1a, the results obtained by running the decision tree algorithm ($LS_{predicted}$) were compared to those of the ILS (LS_{ILS}). The decision tree algorithm that is applied, detects learning styles for each dimension of the FSLSM on a 3-item scale. This scale consists of the values concerning each of the two poles of the specific dimension, as well as the balanced style that falls midway between the two. In simple terms, taking the case of the active/reflective dimension, the 3-item scale consists of an active, balanced and reflective learning style. Similarly, the results obtained from the ILS are divided into 3 equal parts. Thus, students with scores of between 0 and 3 are reflective learners, those with scores of between 4 and 7 are balanced learners and those that have a score of between 8 and 11 are active learners. For measuring the precision of the proposed automatic detection approach, the following formula (4) proposed by García et al. (2007) is used.

$$Precision = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n} \cdot 100 \qquad (4)$$

In (4): n is the number of students. The function Sim compares two parameters, namely $LS_{predicted}$ and LS_{ILS}, and returns 1 if both parameters are equal, 0.5 if one represents a balanced learning style and the other represents a preference for one of the two poles of the dimension, and 0 if they are opposites.

The advantage of the specific measure is not only that it determines precision but also how close the predicted learning style ($LS_{predicted}$) is to the learning style detected by the ILS questionnaire (LS_{ILS}). It is expected that the $LS_{predicted}$ can differ from the LS_{ILS}, this however, does not mean that this difference always has the same importance when one of them is balanced or when they are opposites.

4.6 Data analysis

The aim of our analysis was twofold: first to evaluate the precision of the proposed approach for automatic detection of learning styles (RQ1a) and second, to investigate whether our adaptive mechanism was able to stimulate students to study more (RQ3), and help them to improve their learning outcomes (RQ4) without increasing Moodle's complexity (RQ3).

To answer RQ1a, we compared the precision calculated by formula (4) with the respective values of other similar approaches. Regarding RQ3 and RQ4, we calculated mean and standard deviation values for the data obtained from the relevant instruments. In addition statistical correlation analysis was also employed to the aforementioned data. In order to check for statistically significant differences, a two-tailed t-test was applied for questions or grades where data were normally distributed and a two-tailed Mann-Whitney U test (u-test) for items where data were not normally distributed. The Kolmogorov-Smirnov test was used to check whether data were normally distributed or not. In addition, correlation analysis was employed to investigate student feedback on the recommended adaptive sequence.

4.7 Results

4.7.1 Does the proposed approach for automatic detection of learning styles attain high precision?

To answer RQ1a, the precision of the proposed approach for automatic detection of learning styles was calculated by using formula (4). The precision attained with the proposed approach was 70%, 66%, 75% and 80% for the four dimensions of FSLSM, respectively.

Furthermore, the findings of the comparison between students' responses to the ILS questionnaire and the evaluation questionnaire are presented in Table 7.

Table 7 Comparison between ILS detection and students' responses regarding their learning styles

Active / Reflective	Sensing / Intuitive	Visual / Verbal	Sequential / Global
60%	60%	66%	51%

The results in Table 7 do not dispute the questionnaire's validity but indicate that the detection of learning styles solely via the ILS questionnaire is either error-prone due to students' inaccurate responses or students are unaware of their learning preferences. Consequently, the ILS questionnaire cannot be used on its own.

4.7.2 Does an adaptive mechanism based on learner behavior and knowledge affect system usability and motivational appeal?

The findings regarding system usability and motivational appeal (RQ3) are presented in Table 8 and Table 9 respectively. It should be pointed out that Cronbach's alpha for the two subcategories of the questionnaire was 0.842 and 0.805 respectively, suggesting that the questions have relatively high internal consistency.

Table 8 Student feedback on system usability

	Experimental Group		Control Group		
	M	SD	M	SD	u-test
Pages loaded fast	3.95	0.896	3.90	0.831	U=2276.5 p=0.642
Navigation was easy	4.21	0.858	3.98	0.806	U=1980.5 p=0.07
System was user-friendly	3.99	0.904	4.00	0.856	U=2379.5 p=0.998
Links were definite	4.28	0.851	4.28	0.839	U=2360.5 p=0.932
System was considered adequate for novices	4.05	0.866	3.87	0.957	U=2149 p=0.293
Easily familiarized myself with the system	4.46	0.787	4.36	0.868	U=2500.5 p=0.560

Both the experimental and control groups had relatively similar results regarding system usability (Table 8), indicating that when an adaptive mechanism is embedded in Moodle, system usability is not affected (RQ3). Perhaps one of the most important findings is the last item in Table 8. An average of 4.46 in the experimental group and 4.36 in the control group responded that students found it easy to familiarize themselves with the system, i.e., there was an overall positive response to system usability. It should be noted that there were no statistically significant differences, even for questions that had slightly different mean values.

Table 9 Student feedback on the system's motivational appeal

	Experimental Group		Control Group		
	M	SD	M	SD	u-test
Progress bars motivated me to study more	3.87	1.132	3.07	1.181	U=1448.5 p=0
System motivated me to study more	4.12	0.967	3.62	0.986	U=1679.5 p=0.002
System helped me to learn easier	4.18	0.833	3.87	0.885	U=1890 p=0.027
Quality of educational resources	4.05	0.622	4.06	0.574	U=2384.5 p=0.978
Satisfaction from system's usage	3.96	0.904	3.89	0.985	U=2300.5 p=0.721

As can be seen from the results in Table 9, there was an overall general satisfaction with both the use of Moodle and the quality of the educational resources. In regards to the system's motivational appeal, an average score of 4.12 and 3.62 was given by the experimental and control groups respectively, the difference of which was statistically significant at the 95% confidence level. Those in the experimental group found Moodle helpful in making learning easier than the control at a mean of 4.18 (SD = 0.833) and 3.87 (SD = 0.885), respectively, with a statistical significance (U = 1890, p =

0.027). One of the most important findings in Table 9 is item one on whether the TPC and GPC progress bars motivated students to study more. The difference in the mean score between the two groups was statistically significant (p-value was less than 0.05), with 3.87 (SD = 1.132) for the experimental and 3.07 (SD = 1.181) for the control. Our initial assumption that it was far better to view the progress bars immediately after the content of each section than seeing it in a new window for all the sections, was, therefore, confirmed.

4.7.3 Does an adaptive mechanism based on learner behavior and knowledge improve student performance more than the standard version of Moodle?

Students' mid-term exam grades were analyzed to answer RQ4. Table 10 presents the findings on whether the proposed mechanism helped to improve student performance on the mid-term exam, which was graded out of 30. As can be seen, the experimental group got an average grade of 20.11, whereas the control got 17.33. These findings show that the proposed mechanism did contribute to enhancing student performance. The Mann-Whitney test revealed that this difference was statistically significant with a p-value of 0.039. In addition, the experimental group scored almost double on the TPC with 61.77% than the control group (32.95%), the difference of which was statistically significant at the 95% confidence level. This finding would support that the adaptive mechanism motivates students to become more actively involved in the activity, which strengthens the findings in Table 9.

Table 10 Student grades on the mid-term exam

	Experimental Group		Control Group		
	M	SD	M	SD	u-test
Grade	20.11	6.953	17.33	8.948	U=3572.5 p=0.039
TPC (%)	61.77	27.872	32.95	27.972	U=1977 p=0
GPC (%)	61.72	28.948	41.19	33.106	U=2797.5 p=0

In conjunction to the above analysis, regarding the third subcategory of the evaluation questionnaire, it was additionally attempted to investigate if there is a relation between students' outcomes, their learning styles and the adaptive presentation of the educational material. Three of the questions included were the following.

Question 11: Did you strictly follow the recommended navigation sequence while studying?

Question 12: Is the functionality of the recommended navigation sequence interesting and useful?

Question 13: Do you clearly believe that the recommended navigation sequence suits your learning style?

As can be seen from the results in Table 11, students that strictly followed the recommended navigation sequence –chose 4 or 5 on the scale for question 11- also got an average score of 4.06 and 4.03 on questions 12 and 13, respectively. In contrast, an average score of 2.6 and 2.73 to the above questions respectively was given by students that did not follow the recommended sequence. The specific results would, thus, tend to signify that students were positively predisposed to the usefulness of the suggested sequence. Furthermore, those that followed the proposed sequence of exercises stated that it was best suited to their particular learning style. Statistical correlation analysis was employed so as to further investigate the results in Table 11. Significant correlations were found between the responses to questions 11 and 12 (r=0.773, p=0), and between questions 11 and 13 (r=0.321, p=0.005) which strengthen the Table 11 findings.

Table 11 Student feedback on the recommended adaptive sequence

Answer to question 11	Mean of answers to question 12	Mean of answers to question 13
5 or 4	4.06	4.03
3 or 2 or 1	2.6	2.73

Table 12 presents the findings on whether students who followed the recommended navigation sequence performed better on the mid-term exam. It can be seen that they did perform better with an average grade of 22.42 out of 30 in comparison to the arbitrary sequence of study, with an average grade of 19.61. The t-test revealed that this difference was statistically significant with a p-value of 0.041. Moreover, statistical tests found a significant correlation between responses in question 11 and

mid-term grades (r=0.255, p=0.029).

Table 12 Student grades related to whether following the recommended sequence

Answer to question 11	Grade	TPC (%)
5 or 4	22.42	69.5
3 or 2 or 1	19.61	66.19

5 Discussion

The proposed approach for the detection of learning styles differs from other works in that it calculates students' learning styles by considering not only their responses in the ILS but also their interaction with Moodle. In this way, the disadvantages of each approach that are presented in Section 2 can be overcome. In addition, the usage of Weka in the background enhances system flexibility on account of the fact that it is simple to implement other data mining algorithms. Moreover, in comparison to similar studies (Liyanage, Gunawardena and Hirakawa 2014; Atman, Inceoğlu and Aslan 2009; Şimşek et al. 2010), our sample size was substantially higher which strengthens the validity of our findings.

Table 13 presents the precision of the automatic detection of learning styles attained by eight different approaches including the proposed approach, two data-driven and five literature based approaches compared to the results obtained from the ILS questionnaire. Regarding the proposed approach the results are quite promising (RQ1a) since the attained precision ranges from 66% to 80%. It can be said, therefore, that our approach is suitable for detecting students' learning styles regarding all the dimensions of FSLSM. At this point, it should be mentioned that the precision attained by all the approaches was calculated by using the formula proposed by Garcia et al. (2007) and presented in subsection 4.5. Consequently, the precisions in Table 13 are comparable to each other.

Table 13 Precision attained by different approaches

Approach	Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
Data-driven approaches				
Proposed	**70%**	66%	**75%**	**80%**
Garcia et al. (2007)	58%	**77%**	-	63%
Graf (2007)	62.5%	65%	68.75%	66.25%
Literature based approaches				
Atman, Inceoğlu and Aslan (2009)	83.15%	-	-	-
Simsek et al. (2010)	79.6%	-	-	-
Dung & Florea (2012)	72.73%	70.15%	79.54%	65.91%
Graf (2007)	79.33%	77.33%	76.67%	73.33%
Liyanage, Gunawardena and Hirakawa (2014)	65%	75%	76.25%	77.5%

The next two rows of Table 13 show the findings on precision that were attained by other similar data-driven approaches. As can be seen, our approach attained higher precision in all but one dimension (sensing/intuitive) than the other two approaches. Garcia et al. (2007) attained higher precision regarding the sensing/intuitive dimension compared to our approach; the overall precision though is lower. In contrast, the effectiveness of our approach can be questioned, especially when compared to literature-based approaches (Liyanage, Gunawardena and Hirakawa 2014; Dung & Florea 2012; Atman, Inceoğlu and Aslan 2009; Şimşek et al. 2010; Graf 2007) on the basis that the precision attained is low as can be seen in Table 13. It should be pointed out that although in literature-based approaches, it is necessary to calculate and state the weights in order to represent the importance of a pattern, this is not required in our approach. Thus, no additional effort is required by teachers during course development. Moreover, some of the literature-based approaches (Atman, Inceoğlu and Aslan 2009; Şimşek et al. 2010) detect learning preferences only in terms of the active/reflective dimension of the FSLSM, while the study sample size was only 17 and 27 students, respectively. In Graf's study

(2007) and in (Liyanage, Gunawardena and Hirakawa 2014), although 75 and 80 students participated respectively, the patterns considered were rather complex and demand a substantial amount of extra effort by teachers when creating a course in Moodle. Moreover, the ILS results were divided into 3 unequal parts, of which the second part was almost double the other two. Thus, precision can be challenged on the basis of an inclination towards the balanced style.

In order to accurately detect a learning style from a student's behavior, the student has to first become involved in studying and doing the Moodle course so as to create a significant amount of interaction data. It is meaningless to reach satisfactory adaptation at the end of the course though. It was decided to apply the decision tree algorithm after the second and fourth weeks, and at the end of the course to compare the detection results and check how fast our approach is. The results indicate that even only after two weeks into the course, we were able to accurately detect learning styles. More specifically, the precision attained after the first two weeks for the four dimensions of the FSLSM were quite similar to the values attained at the end of the course.

Summarizing the findings of the evaluation study regarding RQ1a, the conclusion can be reached that the proposed approach for automatic detection of learning styles attained higher precision than similar approaches. The most important finding was that this precision is attained by using a less complex set of patterns, compared to the number of patterns of related works (Graf 2007; Atman, Inceoğlu and Aslan 2009), coupled with a relatively flexible mechanism (Fig. 2). Our proposed approach for automatic detection of learning styles aims to adopt a significantly simpler user model that is generic and can be applied to more LMS.

To answer RQ2, a mechanism suitable for providing adaptive courses to students based on their learning styles and knowledge level was developed to take advantage of the proposed approach for automatic detection of learning styles. The adaptive mechanism was embedded in Moodle so that the sequence and presentation of a course's learning objects can be adapted to students' preferences.

Overall, the results of the evaluation study were quite positive regarding both the approach for automatic detection of learning styles and the adaptive mechanism. RQ3 of this study aimed to investigate whether system usability and motivational appeal was affected by the implementation of the adaptive mechanism. Since more functionalities were added in Moodle, it might be expected that system usability would decrease. Furthermore, since the study participants were first year students, it might be assumed that they would not be accustomed to the use of LMS, and could consequently have difficulty in learning to use the system. However, the findings indicated that both the experimental and control groups had an overall similar positive response to system usability. Moreover, system's motivational appeal was positively affected by the proposed adaptive mechanism (Table 9 and Table 10). There was no need, therefore, to make the system more complex in order to enhance motivation for study in the experimental group, which helped them to achieve better grades than the control in the mid-term exam. Therefore, regarding RQ4, the statistically significant difference in student performance between the two groups indicates that the proposed mechanism has a positive impact on learning outcomes compared to the standard version of Moodle.

The threats to the validity of the empirical study are in the context of construct, reliability and internal validity. A construct validity threat might be related to the formation of the two groups that was based on student numbers, possibly resulting in an imbalance in student distribution for each learning style. However, the results in Table 6 suggest that the construct threat has been mitigated to an extent. Reliability threats are related to the reliability of the evaluation questionnaire used. Cronbach's alpha was calculated for the questionnaire and the results (0.862) indicate that the questionnaire items have a relatively high internal consistency. Internal validity threats are related to confounding factors which might influence the value of the dependent variable (grade in the mid-term exam). Such a threat does apply to the present study, since the performance of a student might have been affected by factors that could not have been measured as they were beyond the study's scope, such as study time, intelligence and general background knowledge. To limit the impact of such factors, performance indicators also include the TPC and GPC measures. Also, the comparable students' academic profiles for both groups, goes towards minimizing this threat. Finally, despite the fact that the validity of the findings might be questioned on the assumption of the subjectivity of student responses on the feedback questionnaire, the TPC values provide a measure of objectivity as regards student involvement. It would have been pointless for students to try to deceive the system as they were not awarded any bonus grades for higher TPC or GPC values.

6 Conclusions

There is a growing tendency to automatically detect students' learning styles either by using data-driven or literature-based approaches. In our contribution to research, a data-driven approach for

identifying learning styles in Moodle is introduced. The proposed approach for automatic detection of learning styles refers to all four dimensions of FSLSM. The findings are promising for the wide use of the system due to the high level of precision attained in conjunction with the added advantages, which include flexibility of the proposed architecture, and that teachers require less effort in application.

Even though the proposed adaptive mechanism and patterns of behavior can be used to adapt other courses, they are sensitive to courseware design. The adaptive mechanism cannot be used, for example, if the course only consists of videos. However, it should be pointed out that the learning styles that are automatically detected by the proposed approach can also be used to adapt other courses even in different subjects. For example, a student's learning style automatically detected in one course in the winter semester can be used to adapt a totally different course to that learning style in the following semester. There is no need for the student to fill in the ILS questionnaire again as the system provides the adaptive course from the start, based on the results of the previous course.

These preliminary findings lay the groundwork for further research in the field of adaptive learning. Our future work will focus on in-depth analysis of our approach, as well as the application of new adaptation techniques and the incorporation of new types of learning objects that promote collaborative learning. There will also be a review of the proposed set of behavioral patterns to pinpoint any possible areas of improvement.

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