Implementation of Moodle plugins to support student's learning styles

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Abstract— **E-learning has been a trend for several years, and LMSs (Learning Management Systems) are more often being used at schools and universities in addition to traditional learning methods. Although they facilitate the work of students and teachers, there are also challenges they both face while using them.**

One of the reasons of these challenges is that students have different background, learning styles, goals etc. It is shown that having materials adapted to student's learning styles in LMSs can facilitate the process of teaching and learning but identifying each learning style and adapting materials based on each learning style is not a very easy task.

In this paper we will show three plugins we have built to enhance Moodle to support learning styles.

The first one is used to identify, and store student's learning styles based on a questionnaire. We have also added two Moodle report plugins: "Learning styles" report that shows a graphical distribution of learning styles between students, and "Activity Report" that shows for each student, the number of interactions with each material, type (pdf, ppt, video etc.) along with each student's learning style. These plugins will be handful to teachers to analyze learning style's distribution for each course and find if there is a correlation of the number of interactions of students with each type of material and learning styles. Using these reports, they can make better decisions and choose appropriate materials for their courses.

In this article we show part of our work in progress to build a fully adaptive module in Moodle, that will adapt courses based on learning styles.

Keywords—Moodle;E-learning;Learning Styles; ILS questionnaire;Plugin

I. INTRODUCTION

Teaching can be very challenging, especially in higher education, because students come from different backgrounds and have different learning styles. When a student is active, highly motivated and in possession of the right strategic knowledge, he can have better results. To help university students to learn effectively, instructors need to know and adapt to different styles of learning [1].

There are many ways of detecting learners learning style, but the traditional way is by questionnaires. We are going to use Moodle to implement the learning style questionnaire approach, because it is an open-source and modular platform, and very easily extended, as we have noted in a previous article [2].

Although there are a lot of theories used to classify students into learning styles groups, we are going to use the Felder-Silverman approach, which is the most used approach.

Felder-Silverman' model (FSLSM) - Felder and Silverman (1988) advocate that students learn in different ways: by hearing and seeing; by reflecting and acting; reasoning either logically or intuitively; by memorizing and visualizing and drawing analogies; and, either steadily or in small bits and large pieces. They also advocate that teaching styles vary, such as an educator's preference for lecturing or demonstrating, or for focusing on principles or applications. According to FSLSM students can be divided in these groups based on their learning styles: active/reflective, visual/verbal, sensing/intuitive, sequential/global [4].

Based on FSLSM approach, a questionnaire called ILS (Index of Learning Styles) questionnaire was developed. (Felder and Soloman, 1997). It contains 44 two choice questions distributed along the four learning style dimensions, where one choice increments and the other decrements the score of the dimension. The calculated value is an integer in the range [-11, +11] since there are 11 questions for each dimension. The ILS questionnaire provides a very precise quantitative estimation of a learner's preference for each dimension of FSLSM [4].

In this paper we are going to describe three plugins we have implemented in Moodle. The first one is used for adding ILS questionnaire, calculating, and storing student learning style automatically, based on their responses. Along with this plugin, we are going to add two report plugins that will help teachers/instructors analyze student's learning styles and activity behaviors in their courses and make better decisions.

II. RELATED WORK

Moodle is a modular open-source LMS that ca be extended using plugins. Plugins in Moodle are add-ons that increase its functionality. There are plenty of plugins for different purposes like: Administration, Assessments, Collaboration, Communication, Content, Interface. There are also a lot of types of plugins such as: Activity module, Admin tool, Block, Editor, Local Plugin, Report Plugins, Course format, Quiz/Access role, Search engine and so on [10].

Moodle is a very popular platform, but it lacks a lot of tracking tools for student's activity. However,

Moodle offers log data which can be used to capture relevant information [3]. Moodle log data contain the time and date it was accessed, the Internet Protocol (IP) address from which it was accessed, the name of the student, each action completed (i.e., view, add, update, or delete), the activities performed in different modules (e.g., the forum, resources, or assignment sections), and additional information about the action [7]. You can add third party plugins to Moodle, to generate reports related to log data. Different investigations have pointed out the need to develop plugins, to increase the metrics and better visualize results for student's progress on the platform [5].

A lot of plugins are built on top of Moodle that use and analyze log data, based on specific needs for teachers and institutions.

For example, in [3] a plugin to count the time students spent in the system or in a specific course was developed. In [5] information gathered from log files is used to implement a plugin for detecting students at academic risk. Teachers can see a report with graphic analysis of student's frequency of access with activities. Based on this analysis they can identity students who are at risk and contact them. In [7] log data was used to investigate correlation between specific activities on the LMS and student grades, it was found that students with a higher frequency of file openings have higher grades. In this study student's activity by gender was also examined, indicating that female students had a higher number of logs.

In some other studies data mining algorithms are applied to log data to extract useful information. For example, in [4], after collecting data from logs using IES module, association rules in data mining are used to adjust educational content for students.

In [8] a module for automatic prediction of learning styles using J48 decision tree algorithm was developed, using WEKA. The aim of the study was to automate the process of learning styles extraction from Moodle learning styles using data mining techniques.

Several investigations and implementations have been made also for incorporating learning styles in Moodle.

In [12] a Moodle plugin which integrated learning styles ILS questionnaire was added at the registration form. The calculated learning styles were used to adapt the courses and present students with a course that matched their learning style.

In [13] ILS was also used for detecting learning styles in Moodle. Student's material usage was also investigated, and this data was used to cluster learners per learning categories of FSLSM. An adaptive user interface was then provided for each learner based on their learning style.

In [11] a plugin that incorporated learning styles as well as analyzed log data was shown. In this work a learning analytic tool was developed for analyzing and visualizing data correlations between student's learning style and their interaction with the e-learning

platform. This plugin was available for both students and teachers. Teachers could use it to adapt materials based on the correlation of learning styles and activity data. Students could also see these data to understand better their learning style and its impact.

III. LEARNING STYLES INTEGRATION IN MOODLE

To implement the first plugin for identifying learning styles we added ILS questionnaire after student's first login. We decided to add the questionnaire only at the beginning because later, we aim to collect data from Moodle logs and update student's learning style according to these data. We also wanted to get all students' responses so the plugin will not allow students to continue to navigate in the course before filling out the questionnaire. In the figure below a screenshot of ILS questionnaire in Moodle is shown:

Fig 1. ILS questionnaire

To calculate learning styles, we followed the ILS questionnaire approach, and stored a calculated value for each dimension in a new table in Moodle database [6].

We mapped students to three labels for each dimension, for example: active, reflective, and balanced. Preferences are defined by numbers ranging from -11 to 11+. This range is a result of the eleven questions asked for each of the dimensions, where an answer might be valued as +1 (when the answer is a) or -1 (when the answer is b), where each question in ILS questionnaire has only two possible answers. The results of the ILS questionnaire are four numbers, with each number representing the position within a particular dimension. This number is calculated from the difference of calculated values, for example if the student's responses in the active dimension is 3 and in the reflective dimension is 7 it means that they are more a reflective learner, and the calculated value is -4.

If the calculated value is in the range [-2, 2] it is considered with no impact and the student is therefore considered balanced on the dimension.

This approach was followed for all dimensions and learning styles for each student were stored in a Moodle database table called "mdl_user_learning_styles", which contains one record for each student, with their unique identifier and learning style for each dimension.

IV. LEARNING STYLES REPORT PLUGINS

We decided to create a report in Moodle that shows learning styles distribution of students, for each course.

To achieve this, we created a new report plugin showing charts of learning styles distribution, for each learning style dimension. In the figure below a part of the report is shown, only for active/reflective dimension:
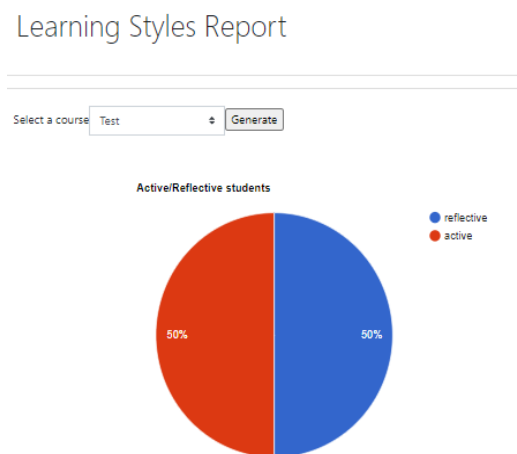

Fig 2. Learning styles report

As we can see from the picture, teacher/admin can choose a course from a dropdown control and click a "Generate" button, to view all charts for each dimension, about students in the chosen course. For example, in the figure we can see that students in the course "Test" are equally divided in active and reflective learners.

This report can be useful to teachers to view how learning styles are distributed between students within their class and to decide about the type of materials they will use in their courses. For example, if there are more than 70% of the students that prefer to learn by visual materials, teachers can add more graphical materials in their courses, to help these students perform better.

In [12] was shown that students who had materials adopted to their learning styles spent less time in the course and had the same scores. This helped the students to learn more effectively and facilitated the learning process. Therefore, adapting materials based on learning styles distribution could be useful.

V. ACTIVITY REPORT PLUGIN

Studies show that questionnaires are not very accurate because students can change their learning style or can give random answers. Therefore, in the future we will build another plugin that will detect student's learning styles based on their activity and update the student's profile. This plugin along with the questionnaire from the plugin we described above will determine student's learning styles more accurately. To show student's activity data and analyze them we first decided to add another report plugin, called "Activity Report".

The report shows number of interactions of students with each material, and type of material (pdf, ppt, video etc.). This report data is taken from Moodle logs. The aim of the report is to track the type of materials students mostly interact with. Along with the number of interactions, name of material, and file type, the report also shows student's learning style for each dimension.

Before the automatic adaptation, it is important to analyze correlations of learning styles with student's activity. The report we showed in this section can be used by teachers to find any correlation between these data and improve their teaching process.

UserName	File Name	File Type	Views	Active/Reflective
student	leksion1	application/pdf	7	active
student	ppt	application/vnd.openxmlformats-officedocument.presentationml.presentation	2	active
student	tt	application/vnd.ms-excel.sheet.macroEnabled.12	2	active
lori1	leksion1	application/pdf	1	reflective
lori1	ppt	application/vnd.openxmlformats-officedocument.presentationml.presentation	1	reflective

Fig 3. Activity Report

VI. DISCUSSION

Our aim is to build a fully adaptive module in Moodle, that adapts materials based on each student's learning style. However, teachers play a significant role in the process of adaptation and can also make decisions about type of materials and content of their

courses. The plugins described in this article will facilitate their process of decision making.

We have decided to build our proposed system with separated plugins. Teachers can use them together as a full module or only specific ones, as they need. The three plugins described in this article are part of the entire module. Teaches can use "Learning Styles Report" and "Activity Report", to make decisions about materials they will have in their courses. They can analyze data of "Activity Report" to understand how learning styles effect student's behavior and find any correlation between them. They can also identify students who are not very active and assist them individually.

These plugins are part of our work in progress to build a fully adaptive module in Moodle. In the future, they can be used in addition to the automatic adaptation module or as standalone tools to support teacher's work.

CONCLUSIONS

In this article we proposed three new plugins for Moodle LMS that can help teachers/instructors to better analyze data within their courses.

We implemented a Learning Style plugin that calculates each student's learning style based on ILS questionnaire and stores it in the Moodle database. We then implemented two report plugins, to visualize these data. The first plugin gives a graphic representation of learning styles distributions of students within each course. The second plugin is an activity report that gathers data from Moodle log files, and shows for each learning material, its file type, and number of views for each student, along with their learning style.

In the future we aim to build a fully adaptive module in Moodle, that adapts materials based on each student's learning style. Along with the questionnaire technique we have built to identify learning styles, we will also update learning styles based on activity data, extracted from log files, like the data shown on the Activity Report. This approach will be more accurate to identify learning styles because it will depend not only on student's responses but also on their activity during the course.

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