ILSA – AN INTEGRATED LEARNING STYLES ANALYTICS SYSTEM

N. Zaric, S. Judel, R. Roepke, U. Schroeder

RWTH Aachen University (GERMANY)

Abstract

Various types of learners can be observed in today’s e-learning environments. Using some of the existing models for the learner type classification, like Felder-Silverman Learning Styles Model (FSLSM), we can identify learners’ preferences and needs and use them to adjust the environment. On the other hand, Learning Analytics can offer insights on a student’s engagement and behaviour, by tracking their actions and performance. We can correlate this data with the data on learners’ type, and use it for deeper user modelling. Supported by visualizations on learning styles and learning behaviour, students and instructors can reflect the learning process. Based on our previously published conceptual model for linking learning analytics and learning styles in e-learning environments, we present an Integrated Learning Styles Analytics system (ILSA), which supports identification of learning styles as well as analysis and visualization of activity data in the Moodle LMS. ILSA consists of a questionnaire for learning style identification derived from FSLSM and offers immediate results to its participants. Next, by utilizing various data sources in Moodle, e.g. log data or the grade book, we are able to correlate a user’s activity and performance with their learning styles. This work offers details on the finalized concept as well as its implementation. By providing insights on data sources in Moodle and presenting various visualizations, this work allows teachers to reuse the system in their e-learning courses.

Keywords: learning preferences, learning analytics, e-learning, learning environments.

1 INTRODUCTION

Learning styles are the ways in which individuals characteristically approach different learning tasks [1]. For the last four decades, investigation on learning styles has been a popular research topic in various disciplines of human training and education, especially in e-learning environments [2]. This concept is closely related to investigation on personalized learning, as a user modelling ‘tool’ in which one user’s profile corresponds to one learning style.

Hence, in our prior work [3], we proposed a conceptual model of a learning analytics tool with the objective to integrate key activities and behaviour data with data on students’ learning styles. The correlation of learning activities and learning styles allows deeper, multilayer personalization, which combines not only the learning styles of a learner but also ones actions and behaviour in a continuous and real-time fashion.

In this work, we use Felder-Silverman learning style model (FSLSM) [4] as a model for identifying learners’ learning styles. This model verifies as a most suitable model to use for studies regarding the Science, Technology, Engineering and Mathematics (STEM) fields [5], which is our target group. Further, we choose to develop this tool for Moodle Learning Management System (LMS), as it is a broadly used, Open Source learning platform, which gives this tool a possibility of reusing by other, interested, institutions or research groups.

Based on the conceptual model for linking learning analytics and learning styles in e-learning environments [3], we present an integrated learning styles analytics system, which supports identification of learning styles as well as analysis and visualization of activity and performance data in the Moodle LMS. This system consists of a questionnaire for learning style identification derived from FSLSM and offers immediate results to its participants. Next, by utilizing various data sources in Moodle, e.g. log data or the grade book, we are able to correlate a user’s activity and performance with their learning styles. This work offers details on the finalized concept as well as its implementation. By providing insights on data sources in Moodle and presenting various visualizations, this work allows teachers to reuse the system in their e-learning courses.

The remaining paper is structured as follows: Section 2 introduces related work in the fields of learning styles, learning analytics and the use of learning styles and activity data in an integrated fashion. In Section 3 the concept and implementation of an integrated learning style analytics system is
presented. Section 4 concludes this work and points out future research opportunities and open questions.

2 RELATED WORK

Research on learning style models is widely used in context of personalization and adaption of e-learning environments and LMSs. In personalization, which, roughly, refers to adjusting learning to satisfy different learners’ characteristics [4], a wide range of characteristics can be used as indicators for personalization but nowadays, one of the most popular indicators are learning styles. Learning style represents different ways in which an individual perceives, process and retains information. Personalization based on students’ learning style is an ongoing topic, and there is a strong acknowledgment supporting the idea that matching instructional design with students’ learning style will positively influence upon one’s performance and general success in learning. The learning styles application in personalization of education can be divided in two directions or categories. One, in which they are used as a base for developing mechanics for the automatic detection of learning styles traces, and second, in which they serve as a tool for instructional design, where course materials and learning objects are adjusted to different learning styles [6].

Over the past few years, automatic-detection of learning styles studies resulted in various models using different artificial intelligence methods to support automatic predictions of the learning styles. For example, in [7] authors used NB Tree Classification to detect the learning style of FSLSM. In [8] Decision Tree and Hidden Markov approaches were used with the same aim. Further, the [6] study describe an approach in which student learning style is predicted based on one’s prior knowledge using the artificial neural network. Further, common researches regarding methods for learning style detection can be found in [9-11]. However, these studies are mainly focused on establishing sustainable framework for clustering learning styles, rather than discussing their influence on learning outcomes and learning process in general. This kind of studies usually presents accuracy and reliability level of their models and its predictions, rather than their practical application.

On the other side, studies, such as [12, 13] are using students’ learning preferences and needs derived from various learning style models as a paragon for instructional design. They rely on the idea that students who learn in an environment that matches their learning preferences will perform better than ones whose learning style mismatch with the learning environment. These studies are mainly developed around the experiment in which one group is subjected to a course that is designed in accordance with one’s learning preferences, and other in which students are confront with the learning materials that do not match their preferred learning needs. At the end, they compare learning outcomes and learners’ behaviour between groups, which then result in a guideline for creating a course that suits different learning styles preferences. Further, a few studies attempted to create an adaptive learning environment, in which adaptation is performed based on students’ learning style category. For example, in [14] authors used “pedagogical knowledge on the didactic domain as well as statistic information on both the student’s knowledge degree and learning preferences” to automatically generate a personalized course. Although it can be promising, using learning styles as a standalone solution for both adaptation and personalization of the course is widely criticized in the community of cognitive psychologists. As they claim, “there is no adequate evidence base to justify incorporating learning styles assessments into general educational practice… further research on the use of learning-styles assessment in instruction may in some cases be warranted, but such research needs to be performed appropriately” [15].

Taking a step back, before any adaptation or prediction, we need to provide an insight on participants’ learning styles and activities, which both (students and instructors) can reflect on. Understanding the correlations between cohorts’ behaviour and learning preferences is of great importance, in order to assist teachers and tutors in decision making regarding student learning experience. In this paper, we present the Integrated Learning Styles Analytics system (ILSA), developed for, and integrated in the Moodle LMS, which aim to collect, match, visualize and deliver data on learning preferences and behaviour to teachers and students.

3 INTEGRATED LEARNING STYLES ANALYTICS SYSTEM (ILSA)

As mentioned above, in our work, we use FSLSM as a frame for identifying students’ learning profiles. FSLSM is a widely used and recognized model for identification of learners’ learning style. In this model, one’s learning style is described based on how he/she accepts, perceives, understands and
processes information. These so-called “dimensions”, constitute the learning styles of an individual based on where they stand on the dimension’s spectrum. Each dimension has two polar definitions: sensing-intuitive for the dimension of perceiving information, active-reflective for the processing dimension, sequential-global for understanding the information and visual-verbal for defining how ones prefer information to be presented. Thus, the framework proposes a spectrum of 16 (2^4) possible learning styles. The spectrums of the four dimensions are described as:

**Sensing**: Involves observing, gathering data through the senses. **Intuitive**: Involves indirect perception by way of the unconscious — speculation, imagination, hunches. **Visual**: Remembers best what they see: pictures, diagrams, flowcharts, timelines, films, demonstrations. **Verbal**: Remembers the information presented is predominantly auditory (lecturing) or a visual representation of auditory information (words and mathematical symbols). **Active**: Involves doing something in the external world with the information - discussing it, explaining it, or testing it in some way. **Reflective**: Involves examining and manipulating the information introspectively. **Sequential**: Follows linear reasoning processes when solving problems. **Global**: Makes intuitive leaps and may be unable to explain how they came up with solutions.

In order to identify learners’ position in each dimension, the authors created the so-called Index of Learning styles (ILS) [4], a self-scoring web-based instrument. ILS contains of 44 questions, 11 questions per each dimension. As a result, this questionnaire exports four numbers (from -11 to +11) which present the tendency to the dimensions’ extremes, where number (+/−) 1 and 3 show mild, (+/−) 5 or 7 moderate and (+/−) 9 or 11 strong tendencies to one or the other extremes. Sign (+ or -) refer to the left or right extreme on the dimension’ scale.

The FSLSM explains that students with mild preferences are well balanced within the dimensions, and that their success does not depend on whether the learning environment coincides with their learning style. Moderate students are probably more effective in the environment that responds to their style of learning, while students who are highly positioned on the dimensional scale have strong preference and fall into a group of students whose success in learning strongly depends on the harmonization of their learning needs and environments offerings.

In [4] authors provide a detailed description on each learning style characteristics, their preferences, how can they be approached and which teaching method corresponds to which learning style. However, in this paper, we will focus only on key learning styles’ characteristics that can be reflected on student’s activities and performance in Moodle LMS. Table 1 summarizes learning objects (LO) and activities that should be tracked and linked with the reflection on different learning style preferences.

<table>
<thead>
<tr>
<th>Resources and activities in the LMS</th>
<th>- Sum of all clicks and downloads of learning resources</th>
</tr>
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<tbody>
<tr>
<td>- Data on quiz participations and results</td>
<td>- Data about video views and views</td>
</tr>
<tr>
<td>- Data on forum visits and posts</td>
<td>- Solutions to exercises</td>
</tr>
<tr>
<td>- Data on chat visits and contributions</td>
<td>- Data on exercise participation and results</td>
</tr>
<tr>
<td>- Data from sheet music book/overview</td>
<td>- Sum of all clicks on external materials/links</td>
</tr>
<tr>
<td>- Total time spent in the LMS</td>
<td></td>
</tr>
<tr>
<td>- Sum of course room calls</td>
<td></td>
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</tbody>
</table>

Some prior research already investigated the integration of FSLSM in Moodle environment. However, either their solutions are not up to date any more, or they focus only on one aspect of the implementation of ILS rather than using learning styles in learning analytics. For example, in [11] authors developed a Moodle plugin, which incorporates the ILS questionnaire into the registration form, after which, the calculated learning style results are used to adapt the course in order to match students’ individual learning style. Further, [12] created a module that uses a custom implementation of the ILS questionnaire and the analysis of all actions performed by the individual user within Moodle, and then provides recommendations for matching course content based on the thusly-determined learning styles.
Our study is in line with the above-mentioned researches on using LS in e-learning analytics; however, there is no evidence on existing Moodle system that provides investigation, analyzation, visualization and recommendation on learning styles to both students and instructors in an interactive and unified way. As so, our system contains of two components: the identification and visualization of the learning styles with recommendations provided to both students and teachers and second, the learning analytics on the identified learning styles for all participants. For further use, ILSA provides exports of raw data and visualizations.

3.1 Learning Styles Identification and Visualization

The first component of the ILSA system has three main features: identification, visualization and recommendations on the learning styles and their preferences. Identification refers to implementation of the interactive ILS questionnaire, where 44 questions are presented one by one to the student. User navigates through the questionnaire with the interactive navigation bar and cannot submit the form unless all answers are given (see Fig.1). In addition, students can fill out the questionnaire multiple times, and all attempts are saved with the calculation and the time each one was taken. After the submission, the calculation of ones learning style is performed based on the algorithm explained in [16] and stored in the database. Each student is identified by the unique ID that, which is known only to one running Moodle. No additional information of the user are processed or stored. Further, the user is given the option to opt-out by deleting all his/her data at any time.

![Figure 1 ILS questionnaire screen](image)

After the identification, both students and instructors can access the results screen. Students get access to their own results as well as the aggregated results of their peers, both available as raw data and in multiple visualizations. The data is presented in different visualizations, including scores specific to either learning styles or learning dimensions and a breakdown of the individual categories for all eight learning styles (i.e., mild, moderate, and strong). Instructors can see aggregated results of all students in their course, can specify a date range to only show matching results, and see how many students submitted the questionnaire (see Fig. 2). Both instructors and students can export the raw data (as a JSON file) or the visualized data in form of a raster image or vector graphics. The identifier of each student's data row is unique for one running Moodle system. No additional information of the user are processed or stored.
In addition to the LS results, both students and instructors are provided with further information. Students have access to explanations for their individual LS, as well as suggestions for their future learning. Students recommendations are given only to students that have moderate or strong preferences to one of the LS, since the ‘mild students’ are considered to be well balanced in any kind of environment. Instructors, on the other hand, can go through suggestions on how to make the best use of various learning material formats in order to provide a suitable learning experience for almost all students. They see recommendations for all learning styles where at least some people in the course are moderate or strong. The threshold for “some” people is 40% of the course, while there is another classification as “many”, which is based on a total of 60% or more [17] (see Fig. 3). Recommendations are written based on detailed guidelines specified in [4].

3.2 Correlation of Learning Styles and Activity Data

The second component of ILSA correlates the learning style data from the first component with students’ activity and performance data. This component provides the analysis features together with the visualizations of results.

3.2.1 Activity and Performance Data Utilization

Activity and performance data refer to records of any user action (online or in the physical world) that can be logged on a computer [18]. In this context, Moodle uses its own event-based logging system1

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1 https://docs.moodle.org/dev/Logging, last accessed 13-03-2019
recording each action as a separate event. An event is an atomic piece of information formed of user id, course id, plugin id, event name (create, view, update, delete) and a description of the event (e.g. the user with id '16' viewed the 'forum' activity with course module id '131'). Further information on a specific event are stored in a central database, which can be accessed by the Moodle data manipulation API\(^2\). This API provides various functions to get records of the databases and further allows inserting, updating and deleting records. The returned records of a getting function are presented as stdClass objects and can be stored locally to be further processed.

Aside from tracking users’ actions Moodle allows recording and using students’ performance data, which are pulled in a decentral fashion. All grades (on assignments, quizzes or workshops) are saved in the Moodle gradebook. The gradebook provides a function to get the grade of a single user (id) for a specific instance of a gradable plugin. This grade information can then be further filtered by the creation time to analyze if performances increase or decrease during the semester. As so, the ILSA system currently offers information on: course activities (course viewed, average grade in course, total time in course and total active time), assignment activities (number of submissions, average grade and feedback visits), quiz/test activities (number of attempts, average grade, best grade, feedback visits, quiz visits), chat and forum activities (discussions created, post created, forum visits), and learning material activities (number of views or downloads for each file type – e.g. pdf, books, compressed files).

### 3.2.2 Correlation and Visualization

The prerequisite for correlating LS with one’s activity and performance data is to import raw data on LS from first to second ILSA component. This could be simply done by a teacher with one click. After the import, both teachers and students have access to the correlated visualization screen. The main screen is visually divided in two sections: at the top - features related to activity and performance data and visualization styles and features on LS manipulation - at the bottom of the screen (See Fig. 4). At the top of the screen teachers get access to all activities and files of the current course, and can choose whether they will see information on LS correlated with one specific event, or comparisons between multiple events. Additionally, activities and files can be grouped (e.g. views on all pdf files in the course). The visualization can further be adjusted by selecting a specific visualization type like a bar chart or a graph and if absolute or relative values should be displayed. Finally, the desired period can be selected (one week, last month, whole semester or custom choose).

\(\text{Figure 4 Visualization part of the second ILSA component}\)

\(^2\) https://docs.moodle.org/dev/Data_manipulation_API, last accessed 13-03-2019
The x-axis on the bar chart in Fig. 4 shows the selected LS preferences while y-axis shows the average quantity of a user's viewings of File 1 (purple series) and the user's viewings of a File 2 within the course (orange series). Teachers only see the correlated data and are not able to see results of a single student. In order to filter the displayed information, the instructor can ‘play’ with various LS selections. Instructor gets to choose from one or multiple LS selection (e.g. strong active and moderate reflective), he can group learning styles (e.g. all active, all global students) or he can use the intersection option to select students who are e.g. strong active and moderate visual. This feature allows teachers to focus on certain groups of learners and see exactly how they behave and which resources they visit in specific period.

Finally, students get to see their own activity and performance data and the overall average data of the respective learning preferences (See Fig. 5). Due to the data privacy conformance they are not able to select and see performing data on learning styles different from their own. Furthermore, it is not possible for a student to see correlated data in the ILSA system if he did not participated in the LS identification.

![Figure 5 Student View Frontend with Example Visualization of Course Visits](image)

4 CONCLUSION AND FUTURE WORK

The Integrated Learning Style Analytics system ILSA presented in this article offers an interactive possibility to determine the LS and to link it with activity and performance data within the Moodle LMS. By using such tool, instructors are given the opportunity to analyse both students’ behaviour and course usage at the same time, all from the pedagogical perspective – by embracing the learning style theory. On the other hand, students are given the opportunity to better understand themselves and the environment in which they learn, as well as how their peers behave in it. This makes it particularly easy for both participant to reflect on the learning process while taking the learning styles into account.

In order to make the ILSA system universally accessible, the next step will be to evaluate the system, through studies and interviews with potential users (both students and teachers). Evaluation should respond to whether the system as such is usable for them, do they consider that this kind of a tool would be useful, and whether the available information and visualizations are sufficiently clear and concrete to extract significant conclusions. In a wider context, evaluation should show whether and how many lecturers are aware of the importance of learning styles and whether they are ready to adopt them as a pedagogical benchmark for further instructional design. The prototypical implementation will be evaluated in blended learning as well as in e-learning course. Both teachers and students should work with ILSA for this purpose. The plugin will also be made available to the Moodle community via official channels.
REFERENCES


[16] NC State University Homepage, https://www.webtools.ncsu.edu/learningstyles/, last accessed 2019/03/10
