Chapter 12
Teaching Improvement Technologies for Adaptive and Personalized Learning Environments

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Abstract Due to the widespread of online learning, learning management systems (LMSs) contain many of online courses but very little attention is paid to how well these courses actually support learners. Teachers build courses according to their preferred teaching methods; on the other hand, learners have different learning styles. The harmony between the learning styles that a course supports and the actual learning styles of students can help to magnify the efficiency of the learning process. In this chapter, an interactive tool is presented for analyzing existing course contents in learning management systems based on learning styles. This tool allows teachers to be aware of the course support level for different learning styles. It visualizes the suitability of a course for students' learning styles and helps teachers to improve the course support level of their courses. It aims at supporting teachers

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in adaptive and personalized learning environments to decide-making efficient modifications in the course structure in order to meet the need of different students' learning styles.

Keywords Interactive course analyzer · Learning styles · Learning management systems

12.1 Introduction

With technologies becoming more and more available and user friendly, educators have been using different technologies in teaching such as computers, courseware, and the Internet to teach students in new and interesting ways. Web technology enables courses to be delivered online to a large number of geographically distributed students, which allows students to learn anywhere and anytime; in addition, designers can produce interactive course materials containing online activities such as self-assessments, animations, and simulations. These can improve learning and are often more enjoyable and meaningful for learners (Hamada 2007). Teachers play a vital role in online learning, they should act as facilitators who guide the students in their learning and offer help tailored to the needs of individuals and groups (Galusha 1997). Despite the popularity of online learning, many problems, such as the students' feeling of isolation and teachers' communication overhead and difficulty in addressing the needs of individuals and groups, may hinder the success of online courses (Rivera and Rice 2002).

In order to successfully fulfill teachers' role in online learning, they need to gain an understanding of what is happening in online courses and become aware of problems experienced by individuals or groups of students (Galusha 1997; Rivera and Rice 2002). However, monitoring students' activities and deciding which actions are most appropriate can be both cognitively demanding and time consuming, and can therefore significantly increase teachers' workload (Helic et al. 2000). Therefore, there is a high demand for automatic feedback for teachers in online courses to highlight important situations, point at potential problems, and recommend appropriate pedagogical activities (Kosba et al. 2007; Macfadyen and Dawson 2010; Romero and Ventura 2007; Romero et al. 2009).

In adaptive learning systems, the common goal is to help students in a personalized way to guide their learning process. An adaptive learning system automatically provides different suggestions, courses, or activities to learners with different characteristics and needs. However, usually the goal of adaptive learning systems is not to replace teachers but to give them more time to devote more one-on-one time to each student and to work with students of varying abilities simultaneously (Gaudioso et al. 2012).

Several approaches for supporting teachers in adaptive learning systems have been presented (Romero and Ventura 2010; Tsai et al. 2001; Vialardi et al. 2008).

The main objective of these approaches is to provide feedback to support teachers in decision making (about how to improve students' learning, organize instructional resources more efficiently, etc.) and enable them to take appropriate proactive and/ or remedial action. Gaudioso et al. (2012) presented a research to show the importance of the teacher support in adaptive educational systems and the useful-ness of both descriptive and predictive models in this assistance. On one hand, the predictive models help the teacher to detect or anticipate problematic situations in the students' learning process. On the other hand, descriptive models allow the teacher to analyze what has happened in a course or in a learning situation. A teacher module was implemented which includes a reporting and data analysis tool (with both predictive and descriptive models). It is concluded that the use of this teacher's module improves the learning process. Moreover, Kosba et al. (2007) presented an approach to support distance learning teachers by offering advice that points at problems faced by students and suggests possible activities to address these problems. This approach utilizes student, group and class models derived from tracking data in web course management systems, and follows a taxonomy of feedback categories to recognize situations that are brought to the instructors' attention. The results of an empirical study in an online learning course point at benefits of the generated feedback to both instructors and students. This, in turn, can have a positive effect on students who can receive feedback tailored to their needs and problems.

In this chapter, we present an interactive tool for supporting teachers in adaptive and personalized learning environments. This tool utilizes our proposed mechanism for analyzing existing course contents in learning management systems based on students' learning styles. It supports teachers to improve the course by making efficient modifications in the course structure. The aim of these modifications is to meet the need of different students' learning styles, which helps adaptive and personalized learning environments to provide personalization and adaptation based on students' learning styles.

Section 12.2 introduces related work that focuses on providing adaptation based on students' learning styles. The course analysis mechanism is presented in Sect. 12.3. In Sect. 12.4, the design and the implementation of the course analyzer tool are illustrated. Section 12.5 concludes the chapter.

12.2 Learning Styles and Adaptive Learning Environments

A student's learning style is defined as a unique collection of individual skills and preferences that affects how a person perceives, gathers, and processes information (Clay and Orwig 1999). Once a learner's particular learning style is detected, it is possible to identify ways to help in improving the learning process (Onyejegbu and Asor 2011). There are many models about learning styles in literature such as Kolb (1984), Honey and Mumford (1982) and Pask (1976). In this research chapter, we utilize the Felder and Silverman's learning style model (Felder and Silverman 1988)

because of its applicability to e-learning and compatibility to the principles of interactive learning systems design (Kuljis and Liu 2005). Furthermore, the Felder and Silverman's learning style model (FSLSM) is one of the most often used model in adaptive educational systems in recent times and some researchers even argue that FSLSM is the most appropriate model for use in adaptive systems (Carver et al. 1999). In this model, Felder and Silverman describe the learning style of a learner in great detail, distinguishing between preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global), where each learning style corresponds to (matches with) one of four teaching styles (active/passive, concrete/ abstract, visual/verbal, and sequential/global). By using dimensions instead of types, the strengths of students' preference toward a particular learning style can be represented. Moreover, FSLSM is based on tendencies, enabling the learning style model to consider exceptional behavior.

Many studies have been conducted to provide recommendations and adaptations for online courses based on learning styles (Paredes and Rodríguez 2004; Graf and Kinshuk 2007; Mejía et al. (2008). Adaptation process to deliver content based on user learning styles. International Conference of Education, Research and Innovation (ICERI 2008). Most of the previous research focuses on identifying students' learning styles and adapting courses based on the identified learning styles. Graf and Kinshuk (2007) introduced a concept to enhanced LMSs with adaptivity based on learning styles. They used the open source LMS Moodle as a prototype and developed an add-on that enables Moodle to automatically provide adaptive courses that fit the learning styles of students. Paredes and Rodríguez (2004) presented a framework that collects explicit information about the students by means of the Index of Learning Styles (ILS) questionnaire developed by Felder and Soloman (1997), adapts the course structure and sequence to the student's profile and uses the implicit information about students' behavior gathered by the system during the course in order to dynamically modify the course structure and sequence previously selected. Experimental results of evaluations of such adaptive systems indicated that providing adaptive courses based on students' learning styles plays an effective role in enhancing the learning outcomes by reducing learning time and increasing learners' satisfaction (Graf and Kinshuk 2007; Popescu 2010; Tseng et al. 2008).

The previous related work presented systems for providing adaptation based on students' learning styles. When a system adapts a course to fit better with particular learning styles, the original course itself should contain suitable learning objects that support such learning styles, otherwise the adaptation mechanism will not be able to provide efficient adaptive course. In order to measure the ability of a course to be adapted for particular students' learning styles, we present a mechanism and a tool to analyze existing course contents in learning management systems. This tool allows teachers to be aware of the course support level for different learning styles. It visualizes the suitability of a course for students' learning styles and helps teachers to improve the course support level of their courses. In addition, the tool can be used to evaluate how well-adapted courses support targeting learning styles.

12.3 Course Analyzing Mechanism

This mechanism aims at analyzing existing course structure and contents in LMS based on the literature from Felder and Silverman (1988), who provide a clear description on how learners with particular learning styles prefer to learn. The mechanism considers which types of learning objects (LOs) support particular learning styles and at which place/location in the course these types of LOs can support such learning styles (El-Bishouty et al. 2012). Basically, this mechanism considers eleven types of learning objects; however, it is flexible so that new types of LOs can be added if necessary. The following list shows the currently considered types of LOs.

- *Commentaries*: provide learners with a brief overview of the section.
- *Content Objects*: are used to present the learning material of the course.
- *Reflection Quizzes*: include one or more open-ended questions about the content of a section. The questions aim at encouraging learners to reflect about the learned material.
- *Self-Assessment Tests*: include several close-ended questions about the content of a section. These questions allow students to check their acquired knowledge and how well they already know the content of the section through receiving immediate feedback about their answers.
- *Discussion Forum Activities*: provide learners with the possibility to ask questions and discuss topics with their peers and instructor. While a course typically includes only one or few discussion forums, the course can include several discussion forum activities as LOs that encourage learners to use the discussion forum.
- *Additional Reading Materials*: provide learners with additional sources for reading about the content of the section, including, for example, more detailed explanations.
- *Animations*: demonstrate the concepts of the section in an animated multimedia format.
- *Exercises*: provide learners with an area where they can practice the learned knowledge.
- *Examples*: illustrate the theoretical concepts in a more concrete way.
- *Real-Life Applications*: demonstrate how the learned material can be related to and applied in real-life situations.
- *Conclusions*: summarize the content learned in a section.

It is assumed that a course consists of several units and a unit can (but does not have to) consist of several sections. One or more instances of the types of LOs described above can exist in each section. A section may (but does not have to) start with a commentary. Subsequently, there is an area before content (ABC) that may include some LOs that aim at motivating the learners and making the section interesting for them. After this area, the content is presented. In the next area, namely area after content (AAC), different types of LOs may be presented. The conclusions

of the section can be either right after the last content object or at the end of the section.

The presented mechanism recognizes how well a section of an existing course fits to each of the eight poles of FSLSM (i.e., active, reflective, sensing, intuitive, visual, verbal, sequential, and global) by calculating the average of three factors: the availability, the frequency, and the sequence of the learning objects in that section. Consequently, the calculations are applied for each section and then summarized for each unit and for the whole course.

$$\text{Ava}_{\text{ls}} = \frac{(\# \text{ of existing LO types that support ls})}{(\# \text{ of LO types that support ls})} \qquad (12.1)$$

$$\text{Freq}_{\text{ls}} = \frac{(\# \text{ of existing LOs that support ls})}{(\text{frequency threshold})} \qquad (12.2)$$

$$\text{Seq}_{\text{ls}} = \frac{\sum_{i=1}^{n} f_{\text{ls}}(\text{LO}_i) \times w_i}{\sum_{i=1}^{n} w_i}, 0 < w \leq 1 \qquad (12.3)$$

Certain LO types can support diverse learning styles; on the other hand, it is possible that they have no effect. Table 12.1 shows the learning object types that fit with each learning style. The availability of types of LOs is considered as a factor to infer the learning styles that a section of the course fits well. The availability factor measures the existence of LO types that can support each learning style (ls) in a section with respect to all types of LOs that support the particular learning style. The availability factor is calculated using Formula 12.1. On the other hand, the frequency factor measures the number of LOs in the section that support each learning style in respect to the frequency threshold. The frequency threshold represents the sufficient number of LOs in a section to fully support a particular learning style. This threshold is predefined and can be adjusted by the teacher if needed. If the number of LOs that support a particular learning style (ls) in a section is less than the value of the frequency threshold, then the frequency factor is obtained by Formula 12.2, otherwise the frequency factor takes the value 1, which means a full frequency support level for that learning style. The obtained values for both, the availability factor and the frequency factor, range from 0 to 1, where 1 indicates a strong suitability for the learning style and 0 means no support.

The sequence factor measures the suitability of the sequence of LOs for different learning styles. The sequence factor is calculated for each LO according to its type, location (ABC or AAC), and position within ABC/AAC. It is determined according to how well this object type in that place fits with each of the eight learning styles of FSLSM. The sequence factor for each learning style is calculated using Formula 12.3. In this formula, $f_{\text{ls}}(\text{LO}) = 1$, if the LO is suitable for that learning style at that location, and $f_{\text{ls}}(\text{LO}) = 0$ otherwise. n is the number of LOs in the section. The weight w

Table 12.1 The relation between the learning object types and the learning styles

Learning object/learning style	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Reflection quizzes		x		x				
Self-assessment tests	x		x					
Discussion forum activities	x					x		
Additional reading materials		x		x		x		
Animations	x		x		x			
Exercises	x		x					
Examples		x	x					x
Real-life applications			x					x

represents how well the position of a learning object in AAC/ABC fits to the learning style; it is calculated by measuring how far the position of the LO is away from the content. Formula 12.3 represents the weighted mean of f_{ls}(LO). Its value ranges from 0 to 1, where 1 indicates a strong suitability for the learning style and 0 means no support.

12.4 Course Analyzer Tool

The course analyzer is a tool for visualizing the suitability of a course for students' learning styles (El-Bishouty et al. 2013). Furthermore, it provides the teachers with an interactive graphical user interface (GUI) that allows them to play around with the course structure. This interactive interface supplies the teachers with drag and drop utility to add, move, and/or remove LOs, and based on any modification simulates the expected changes in the course support level for diverse learning styles. This interactive interface aims at helping teachers in improving the support level of their by making efficient modifications in the course structure. The course analyzer tool is implemented as a web application. It is mainly developed using MySQL relational database management system and PHP scripting language. In addition, Google charts online library is utilized for building the visualization component.

12.4.1 System Architecture

The proposed system architecture of the course analyzer tool is designed to extend the functionalities of any LMS. As shown in Fig. 12.1, the system architecture is illustrated in three layers. The first layer is the data layer; in this layer an internal database is created to store additional data independently from the LMS database. This internal database facilitates a reliable way of storing and exchanging the data among the tool components. The internal database stores extra metadata about the types of learning objects, enrolled students' learning styles, and the analysis results of LMS courses. Let us consider Moodle LMS as an example. Nine Moodle database tables (page, question, quiz, label, lesson, resource, url, user, and course) are extended and linked to the corresponding tables in the internal database (page_extend, question_extend, quiz_extend, label_extend, lesson_extend, resource_extend, url_extend, user_extend, and course_extend). For example, each LO that exists in the page table has a corresponding record in the page_extend table to store its type (one out of the 11 types of LOs illustrated in Sect. 12.3). Also, the course analysis results are stored in the course_extend table and students' learning styles are stored in user_extend table.
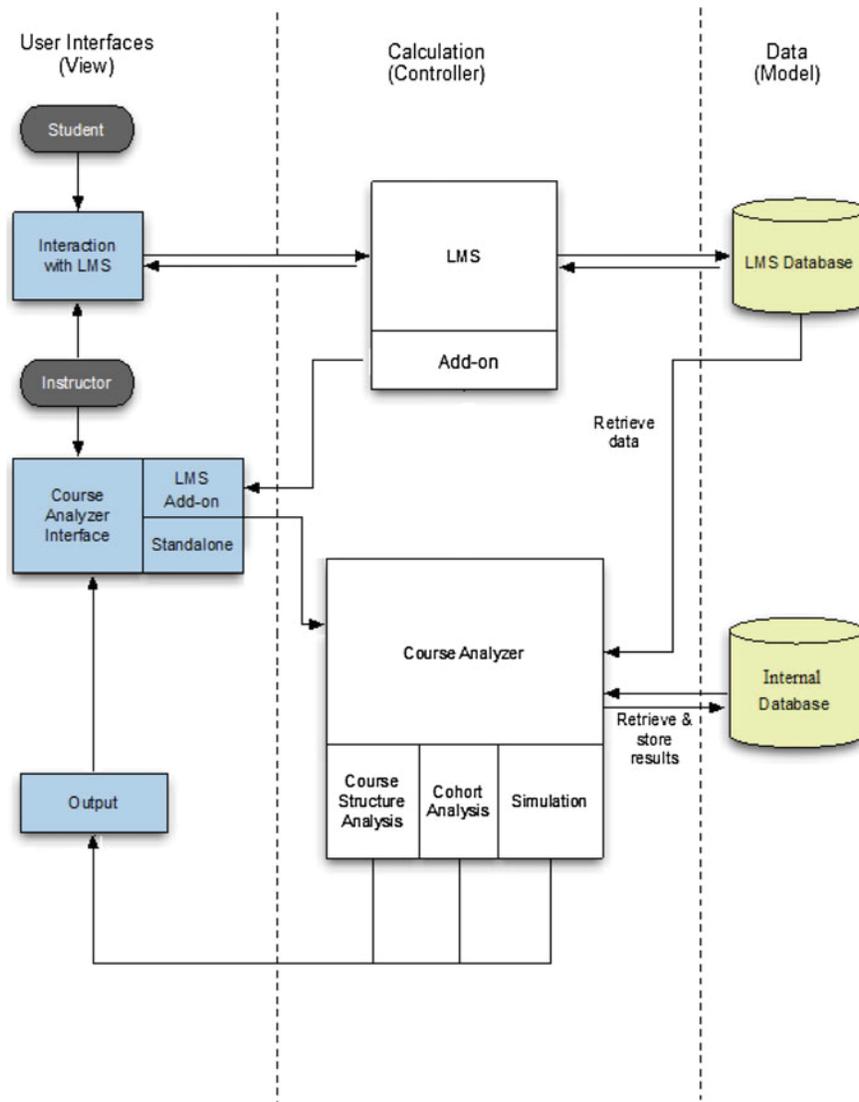
Fig. 12.1 System architecture of the course analyzer

The second layer contains the calculation components. The calculation layer of the course analyzer is comprised of three modules:

- Course Structure Analysis module: it connects to the LMS database, retrieves existing course structure data, applies the proposed analysis mechanism for the course (as illustrated in Sect. 12.3), and stores the analysis results in the internal database.

- Cohort Analysis module: as students' learning styles can be calculated through, for example, the ILS questionnaire (Felder and Soloman 1997) or by a tool like DeLeS (Graf and Kinshuk 2009) and then stored in the internal database, this module connects to the LMS and the internal databases, retrieves the list of students enrolled in each course and their learning styles, and analyzes students' learning styles in comparison with each course support level. This module aims at identifying the course support level for the students based on their learning styles.
- Simulation module: this module considers the teacher's proposed modifications in the course structure and simulates the changes in the course support level for students' learning styles. These modifications are not actual modifications in the course but are only visible in the course analyzer to show how the course support level would change if such modifications would be done in the course.

The third layer is the user interface. There are two methods to access the course analyzer interface. The first method is embedded into the LMS interface through an add-on that works for a particular LMS (a block in case of Moodle), which provides a direct link to the course analyzer interface. This method automatically retrieves the teacher's authentication information from the LMS, and adapts the interface for the teacher's current course and students enrolled in that course. The second method is a standalone web application that requires entering the authentication information manually (such as the user name and password to access the LMS and the internal databases). The later method considers all existing courses in the LMS database; it targets administrators, who would like to access the analysis results for different courses. This chapter focuses on the first method, which is embedded into the LMS interface. The course analyzer interface allows teachers to modify the course structure and visualizes the analysis results.

12.4.2 Visualization Component

The visualization component presents the analysis results and shows how well a course fits with students' learning styles. There are two visualization modes: the General Mode and the Cohort Mode.

The General Mode visualizes the support level of a course for diverse learning styles based on FSLSM. Figure 12.2 illustrates the visualization component of the course in General Mode. This component consists of two parts. The upper part of a component consists of a set of bars to show the strength of the harmony of the course with each of the eight learning style poles (i.e., active, reflective, visual, verbal, sensing, intuitive, sequential, and global), in terms of percentage (calculated by the average of the three factors illustrated in Sect. 12.3). Each learning style dimension is represented by two horizontal bars, one for each pole, where the two poles show the two different preferences of the dimension. The longer the bar, the more the course fits with the learning style. The lower part of a component contains
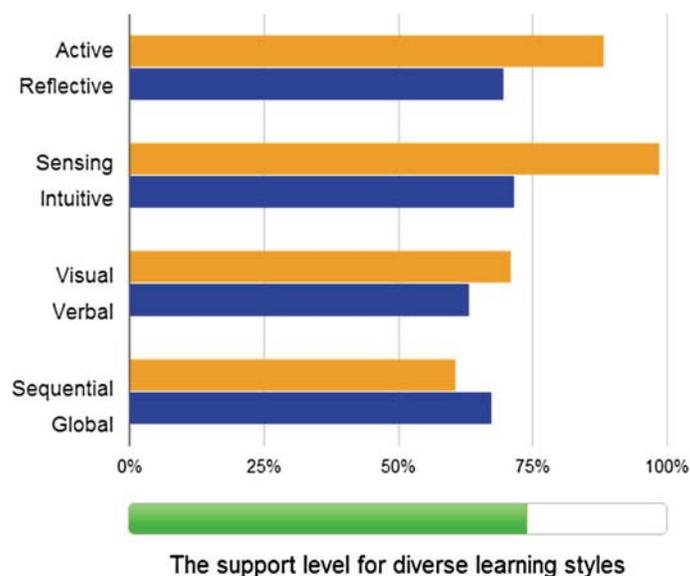
Fig. 12.2 Visualization of general mode

only one bar that shows the overall support level of the course for diverse learning styles (calculated by the average of the support level of the eight poles). Once the teacher moves the cursor over any bar, a tooltip appears to display more details about the analysis factors illustrated in Sect. 12.3.

The Cohort Mode visualizes the support level of a course in respective to the learning styles of the cohort of students enrolled in that course. Figure 12.3 illustrates the visualization component of the course in Cohort Mode. The component visualizes the data about students' learning styles in comparison with the course support level (calculated by the average of the three factors illustrated in Sect. 12.3). As shows in Fig. 12.3, each learning style dimension contains two bars; the upper one shows the course support level for each poles of that dimension (e.g., the active/reflective dimension); the lower bar shows the learning styles of the respective cohort of students on this learning style dimension. In case that all students are fully supported in the course/section, the bar will be displayed in green color, otherwise a gap will be shown in red. The intensity of the red color indicates the number of unsupported students.

12.4.3 Interactive GUI

As shown in Fig. 12.4, the course analyzer interactive GUI consists of two parts: the settings part (at the left side of the interface) and the visualization part (at the right side of the interface). The Analysis Settings area, allows the teacher to switch
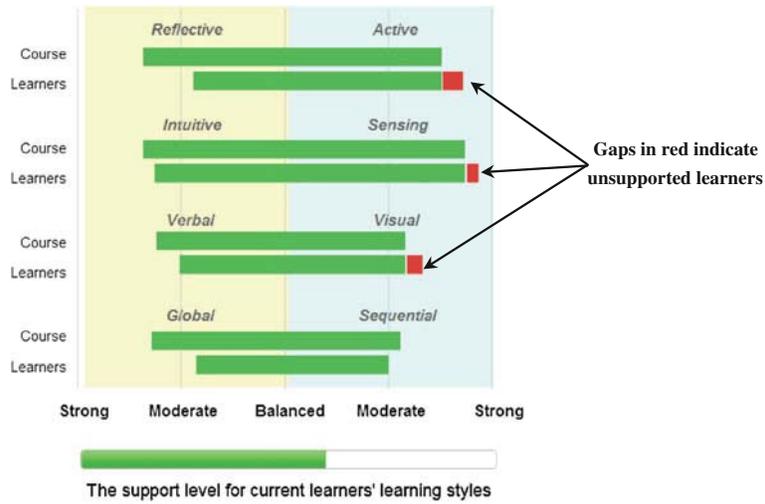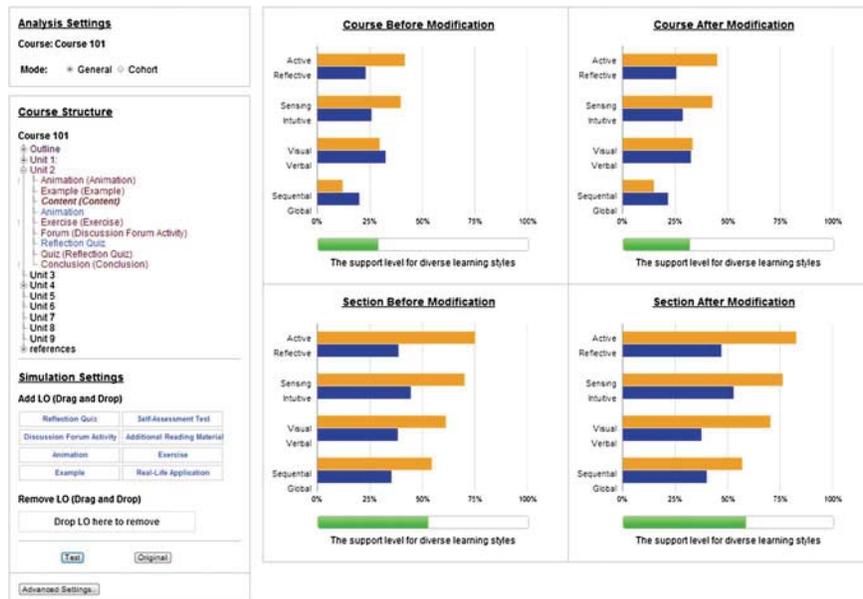
Fig. 12.3 Visualization of cohort mode

Fig. 12.4 Course analyzer interactive GUI

between general and cohort visualization modes (that are explained in Sect. 4.2). In the Course Structure area, the course structure is displayed in terms of units, sections, and a list of LOs in each section. The teacher can browse the course and

select a particular unit/section by clicking on it. The Simulation Settings area allows the teacher to simulate modifications in the course structure. By utilizing drag and drop functionality, the teacher can drag learning objects from the list of learning object types and place them in certain positions in the Course Structure area (displayed in blue), drop learning objects from the Course Structure area to remove them, and/or move leaning objects from one place to another in the Course Structure area (displayed in brown). Once the teacher has completed the modifications on the course structure and wants to analyze how his/her modifications change the support level of the course, he/she can click on the Test button. Then the tool analyzes the course structure and updates the visualization part respectively. Furthermore, in the Advanced Settings area, teachers can set the value of the frequency threshold and select the learning object types to be considered while analyzing the course support level.

The visualization part consists of four similar visualization components according to the visualization mode (for example, the General Model), as shown at the right side of Fig. 12.4. The visualization part shows how well the course and a particular selected unit/section fit with students' learning styles. The upper two of the components visualize the course support level for the whole course before and after the modifications made by the teacher in the course structure. Similarly, the other two components show the selected unit/section support level before and after the modifications.

12.4.4 System Usage

In order to be aware of how well an online course fits with students' learning styles, a teacher needs to login into the LMS using his/her username and password, and then navigate to the course webpage. In that webpage, the teacher can easily find a link for the course analyzer tool (given that the add-on of the tool is already installed on the LMS). The teacher can click on that link to launch the course analyzer. Consequently, the course analyzer retrieves the course structure data, analyzes the course based on learning styles, retrieves the learning style data of students enrolled in that course, and then visualizes the course support level for diverse learning styles in General Mode. The teacher can switch to Cohort Mode to visualize the course support level for enrolled students' learning styles. The teacher can use the simulation settings to improve the course support level for particular learning styles and fill any gaps by adding, moving, and/or removing LOs, and then can click on the Test button to visualize the expected changes in the course support level. Once the required support level is reached, the teacher can navigate to the course webpage in the LMS and actually can implement the necessary modifications in the course structure to improve the course support level for students' learning styles. Consequently, the course will be ready to apply personalization and/ or adaptation mechanism (for example, using one of the illustrated systems in Sect. 12.3) based on students' learning styles.

12.5 Conclusions

Despite the popularity of online learning, very little attention is paid to how well these courses actually support learners. When designing instructional material, it is important to accommodate elements that reflect individual differences in the learning process. One of these elements is learning styles.

Several systems have been presented for providing personalization and adaptation based on students' learning styles. When a system adapts a course to fit better with particular learning styles, the original course itself should contain suitable learning objects that support such learning styles, otherwise the adaptation mechanism will not be able to provide efficient adaptive course.

In this chapter, we present an interactive tool for supporting teachers in adaptive and personalized learning environments. This tool utilizes our proposed mechanism for analyzing existing course contents in learning management systems based on students' learning styles. Furthermore, it provides the teachers with an interactive graphical user interface that allows them to play around with the course structure. This interactive interface supplies the teachers with drag and drop utility to add, move and/or remove LOs, and thus simulates the expected changes in the course support level for the learning styles. This supports the teachers to decide which modifications should be implemented in the actual course structure. The aim of these modifications is to meet the need of different students' learning styles, which helps adaptive and personalized learning environments to provide personalized and adaptive courses based on students' learning styles. In addition, the tool can be used to evaluate how well-adapted courses support targeting learning styles.

The future plans of the research includes proposing a mechanism to provide teachers with recommendations on how to best extend their courses to support more students with different learning styles, and to fit the course to the current cohort of learners. In addition, experiments with teachers are planned to evaluate the efficiency and the user-friendliness of the tool.

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