26 Redesigning e-Learning Courses: A Student-centered Approach

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26.1 Abstract

In this paper we present a student centered approach for redesigning e-learning courses through the analysis of students' preferential structures. Our approach analyzes the students' preferences in the following dimensions: (a) the dimension of students' learning behavior, (b) the dimension of students' learning performance, and (c) the dimension of students' feedback. Students' preferences are identified before they are exposed to the e-learning course using the Criteria Weights Assessment through Prioritization (WAP) method from the domain of Decision Making. The WAP method provides a valuable source material that includes weights of individuals' preferences that become input in a clustering process that determines clusters, i.e. groups of preferences among students. Based on these clusters we analyze their behavior in the other three dimensions and we provide a framework for the decision maker capable to provide significant feedback for the redesign process of the course.

26.2 Keywords

Redesign e-learning courses, Weights Assessment through Prioritization (WAP), e-Learning courses, analyzing students’ preferences, learning analytics.

26.3 Motivation

The emergence of new trends such as "Open Educational Resources" and "Open Courses" made possible the so-called "wrapping" of a course around a variety of online learning resources developed by third parties, instead of the from scratch production of learning material (Caulfield, 2012; Fisher, 2012; Koller, 2012; Mangan 2012; Shirky, 2012). For example, Greek universities recently developed, under the framework of the "Open Courses" program, an impressive repository containing more than 3600 courses with open access that can be used complementary to the teaching in the classroom in an effort to improve the efficiency of the courses in higher education. These courses incorporate a wide variety of open resources such as video-lectures, self-assessment exercises, podcasts and other multimedia content resulting in a very large repository of Open Educational Resources (Open Academic Courses Project, 2016) (Psaromiligkos et. al., 2016). In such a context it is vital as well as challenging to design and even more to redesign engaging e-learning courses.

Recent advances in education demonstrate at a great extend the student-centered and personalized dimension of learning. Although technology has many potentials to satisfy such requirements in practice it has been proved a difficult task. Given the numerous e-learning resources an instructional designer is facing a big challenge: "how to design/redesign the appropriate mix of learning activities that will satisfy the students' preferences in order to increase motivation and engagement and finally enhance the learning performance?" The design/ redesign process is an iterative process because the final product is a "moving target". During this process a designer needs sophisticated support and a well designed methodology in order to evaluate the various alternatives. Learners' perception is central in such a process (Jung, 2011) (Dondi et al., 2006) (Ehlers, 2004) (Cashion and Palmieri, 2002).

In this paper we present a decision support approach for redesigning e-learning courses through the analysis of students' preferential structures. We see an e-learning course as a system (Moore et. al., 2005) that is comprised of the following interrelated subsystems (1) the human subsystem (2) the web-based learning resources subsystem, and (3) the technological infrastructure subsystem. Our approach analyzes the students' preferences in the following dimensions: (a) the dimension of students' learning behavior, (b) the dimension of students' learning performance, and (c) the dimension of students' feedback. Students' preferences are identified before they are exposed to the e-learning system using the Criteria Weights Assessment through Prioritization (WAP) method from the domain of Decision Making (Spyridakos et. al., 2016) (Tsotsolas et. al., 2016). The WAP method provides a valuable source material that includes weights of individuals' preferences that become input in a clustering process that determines clusters, i.e. groups of preferences among students. Based on these clusters we analyze their behavior in the other three dimensions and we provide a framework for the decision maker capable to provide significant feedback for the redesign process of the course.

In the next section we discuss in more detail the theoretical background of our approach. We also describe analytically the application of our approach in a real case study at Piraeus University of Applied Sciences. Finally, conclusions and feature research directions are provided in the last section.

26.4 Methodological Approach

The framework of our approach is student-centered and it is consisted of the following four dimensions: (1) students' learning preferences (2) students' learning behavior, (3) students' learning performance and (4) students' evaluation of the underlying learning effectiveness (feedback). The first dimension tackles the problem of how to identify groups of preferences among the students. Based on these groups of preferences, the second dimension examines their behavior in the learning environment. The third dimension examines the actual performance of the underlying groups of preferences while the fourth dimension takes under consideration quality issues of the offered learning activities and resources of the course as perceived by students. The Model of our approach is depicted in figure 1. In this paper we present the way we have analyzed the students' learning preferences and the students' behavior in a real course at PUAS consisted of 149 students using the Moodle Learning Management System.

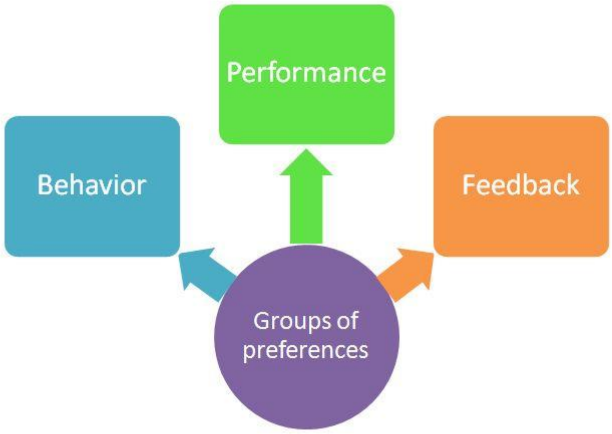


Figure 1: A Model for the Analysis of Students' Preferences

26.4.1 Identifying groups of preferences using WAP

In order to capture the students' preferences we asked them to rank the different types of learning activities that were offered in the course, by assigning a number from 1 to 5, with 1 being the first choice in the hierarchy of preferences. In the effort to hierarchically position the types of learning activities, each participant had the opportunity to define subsets of learning activities by assigning to more than one activity the same preference number, with the sole restriction that at least two subsets of activities should exist in the hierarchy (they could not rank all the different type of activities in the same position). With this process, each participant by completing the prioritization of learning activities identified his personal criteria-preferences in learning activities types (figure 2). Next, having prioritized the personalized criteria of learning activity types, each participant determined a preference range (figure 3), minimum and maximum value, which expressed the relative significance between two successive criteria (1st to 2nd, 2nd to 3rd, etc.).
Thus, having the preference range from a pair comparison of the individual criteria, we applied an indirect estimation method from the field of Decision Making, which is an enhancement of Simos and Revised Simos Methods (Simos, 1990a, 1990b, Figuera and Roy, 2002), the so called «criteria Weights Assessment through Prioritization (WAP)» (Spyridakos et al., 2016) in order to extract the weights of the preference criteria for each student.
WAP method presents improvements over other methods because instead of requiring the Decision Maker to specify the difficult to comprehend and quantify ratio z that expresses the relative significance of a pair comparison of successive criteria or subsets of criteria of equal importance, it requires to determine minimum and maximum values, that is intervals [zmax, zmin], for each pair of successive criteria or subsets (figure 3).

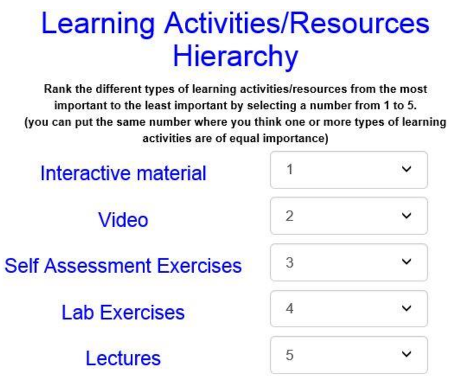


Figure 2 : Learning Activities/Resources Hierarchy

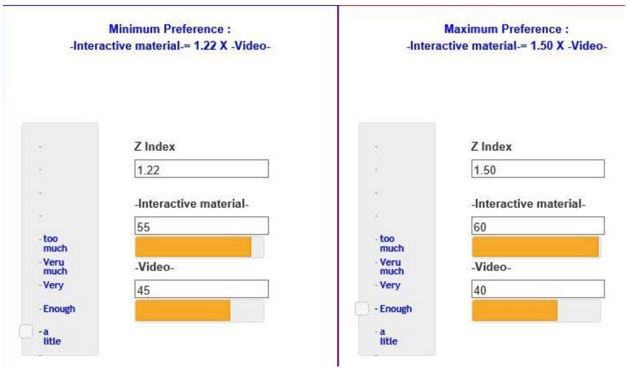


Figure 3 : Relative Importance of successive criteria

The range [zmax, zmin] from the pair comparison of the criteria determines the z ratio for each successive pair so that zminr ≤ zr ≤ zmaxr and pr= zr pr+1. Having thus identified the interval for the z ratio for each pair of successive criteria or subsets of criteria of equal importance, a linear problem is constructed and solved. In reality solving the linear problem leads to the identification of minimum and maximum values for the weights of the criteria, that include an infinite number of solutions, that is vectors of weights, that form a hyper-polyhedron (figure 4).

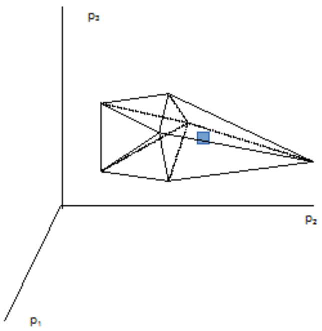


Figure 4 : hyper-polyhedron of solutions

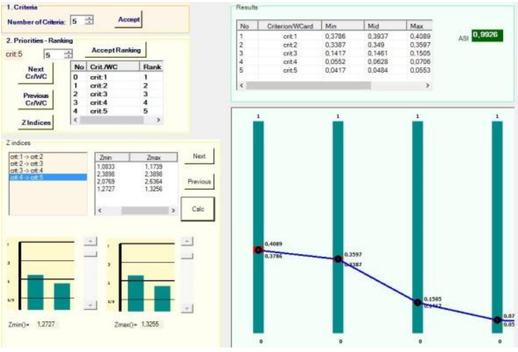


Figure 5 : Criteria Weights estimation

WAP ultimately results in determining the barycenter of the hyper-polyhedron reaching at a satisfactory degree of accuracy for the criteria weights and having high indicators for the robustness of the solution, such as the Average Stability Index (figure 5).
The analysis concludes by performing a Cluster Analysis in SPSS for the criteria weights which led us to the identification of groups of students according to their preferences of the types of learning activities that were offered in the course. The analysis revealed (tables 4, 5) 5 distinct groups with different preferences for the different types of learning activities offered in the course.

Table 4: Cluster Centers

	Cluster				
	1	2	3	4	5
Scorm	0.39	0.13	0.14	0.17	0.14
Video	0.25	0.14	0.22	0.17	0.12
SelfAssessment	0.14	0.15	0.39	0.20	0.15
LabExercises	0.13	0.17	0.15	0.25	0.46
Lectures	0.09	0.41	0.10	0.21	0.13

Table 5: Number of Cases in each Cluster

Number of Cases in each Cluster			
Cluster	1	49	33%
	2	23	15%
	3	25	17%
	4	17	11%
	5	35	23%
Valid		149	100%

The 1st group showed a preference clearly oriented to interactive material learning activities (39%) and a smaller preference to videos (25%), and consisted the 33% of target group of our research. The next in population group, 23% of the population, was the 5th group of the Cluster analysis which showed a particular preference in laboratory exercises. The 2nd group turned its preference towards face-to-face lectures and accounted for the 15% of the population. The 3rd group, in which we had a participation rate of 17% of the total population, indicated preferences towards laboratory exercises (39%) and Video-Lectures (22%). Finally, the 4th group, with the lowest population rate of 11% of the sample, presented an equal distribution regarding its preferences for the various types of learning activities in the course. A schematic representation of the five different students' groups of preferences is depicted in figure 6.

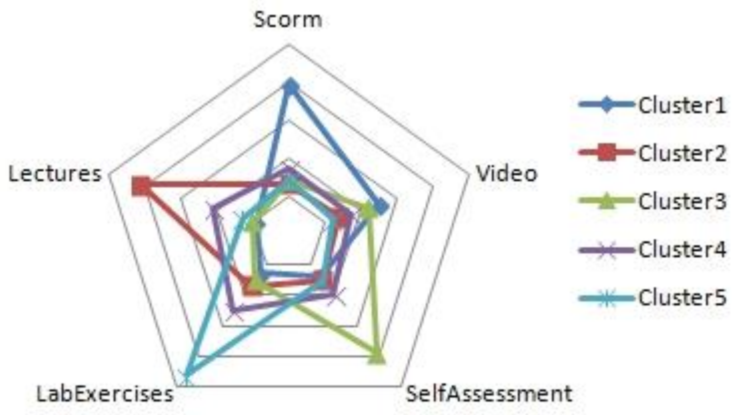


Figure 6: Illustration of preferences groups

26.4.2 Analyzing Students' Behavior

The identification of the groups of preferences in our approach is the keynote and the starting point of our analysis. After identifying groups of preferences we proceed to analyze their behavior in the three aforementioned dimensions. Each dimension constitutes a separate area and needs specific instruments and tools in order to support the decision maker. The first dimension that concerns the behavior of students in the e-learning environment needs tools and techniques from the Learning Analytics area (Larusson and White, 2014). Learning Management Systems could be the ideal platform for learning analytics because they can hold all these complex interactions between learner-learner, learner-content, and learner-educator during the instructional process (Psaromiligkos et al, 2011). In our case the e-learning environment was the Moodle Learning Management System and we have developed a specialized module (plugin) in Moodle that provides various reports (mostly visual) to the decision makers (Kytagias et al., 2015) in order to make them able to analyze the behavior of the groups of the students as they were formed in the previous dimension of our analysis. For the second dimension, in order to capture students' feedback we developed an on-line questionnaire about the quality of the learning activities that they were exposed (inside Moodle) and we asked the students to fill it in at the end of the course. Finally, for the dimension of the students' performance we analyzed the data collected from the final course marks of students.

More specifically, in our effort we created in Moodle the five groups of students that were formed in the previous analysis based on their profile of preference regarding the different types of learning activities and we executed various reports to compare the behavior of the groups in each type of activity (see next Figures).

Figure 7: Scorm Usage

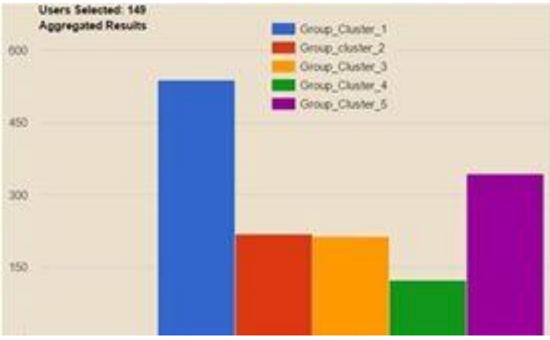


Figure 8: Video Usage

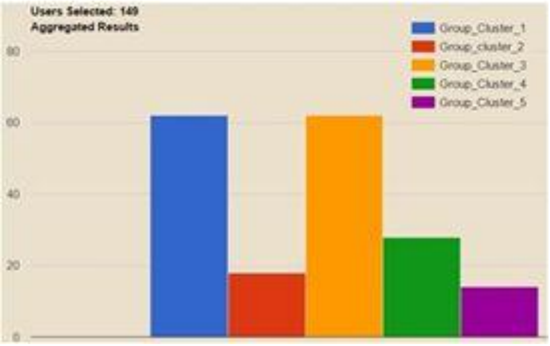


Figure 9: Self Assessments Exercises Usage

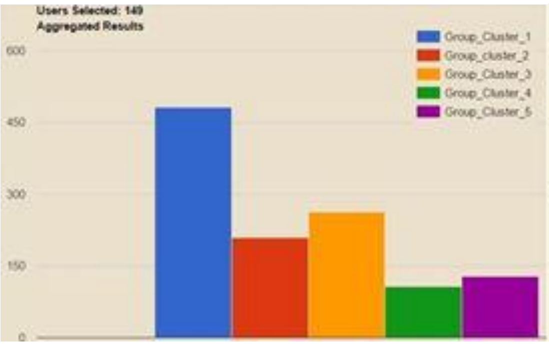
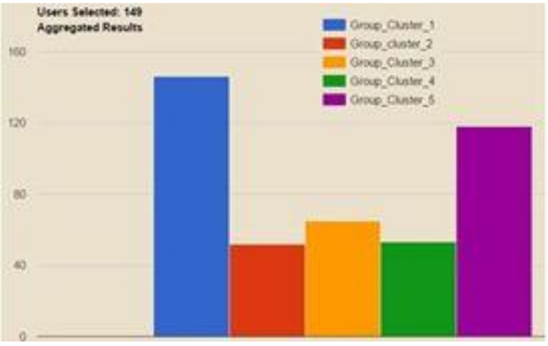


Figure 10: Lab Exercises Usage



From the underlying reports we are able to notice that the 1st group (blue color) of students, which showed the greatest preference in scorm activities (interaction material), was actually the most engaged in this type of activities. The 2nd group (red color) stated its preference in face-to-face activities that is activities in traditional lectures that are not recorded in the Learning Management System. The 3rd group (orange color), which was characterized by a strong preference for activity types of self-Assessment (39%) and at lesser degree for Video activities (22%), and showed to be more engaged in Video activities than in self-Assessment activities. Regarding the Video activities in the course we noticed that the groups that showed preference to this type of activity, ie. the 1st group with preference (25%) and the 3rd group with preference (22%) actually presented the highest usage in this type of activities. The 4th group (green color) showed an equal distribution regarding its engagement in the different types of activities, which is in agreement with its preferences. The 5th group (purple color) expressed a particular preference for the learning activity type of laboratory exercises which is consistent with the overall behavior of the group but we noticed that in laboratory exercises greater involvement presented the 1st group. If we analyze the completion rates as well as the time spent in the above activities we see a little different picture. The first three groups showed the highest completion rates while the last two groups (4th and 5th) showed the lowest. Completion means that the student had studied the whole learning object and not just visited the content. Completion rates we can have at SCORM activities or in activities of Moodle having enabled the "activity completion" attribute settings of the activity. We prefer the first option because it gives more accurate results through the use of specific SCORM attributes (completed, incomplete, not attempting, and so on).

Also, regarding the students' behavior in the e-learning system, the Video type activities presented the lowest number of visits and completion rates and by crosschecking the feedback for this type of activities we also observed a lower rating in comparison with the rest type of activities (see figures 13-15). That footnote provided us with an indication that this type of activities needs improvement. By analyzing the feedback dimension and more specific the feedback taken from questionnaires we concluded that the packaging of the Video learning resources were too lengthy in time and it was not usable for the learners, who most of the times were looking for very specific information inside the video files.

As for the dimension of the students' performance, as we have mentioned, we analyzed the data collected from the final course marks of students. Having a close look at the achievements of the students we see that the 2nd group had the best average grade while the 4th group, the group that shows an almost equal preference in the various activity types, showed the lowest performance indicator (near the pass level). This situation allows us to characterize this group as the most risky for not successfully completing the course. Decision maker needs to analyze further this group by crosschecking the underlying learning behavior as well as the feedback gave on the activities. We can see that this group had in general low usage and completion rates (except videos' usage) as well as low feedback rates on the various activity types (except lab exercises). This means that this group faced various difficulties that need further analysis. For example, the group may include students that have difficulties because of lower background. This point partially confirmed since we found that several of the students of this group came from other universities (student transfers due to financial problems) with different background. This group found more attractive the lab exercises and it showed a relatively high traffic to video lectures that give us points of improvement. We could also enhance our assessment methods in order to give this group more engagement options in order to increase its performance achievement.

Providing an overall view regarding the feedback and performance dimensions we distinguish the 2nd group (with preference in Lectures) which shows the highest engagement and completion rates in almost all the activity types, except the video ones, and achieved the highest marks regarding its performance. This group seems to include the students which are most engaged, come to lectures, and in general they manage to perform best in all suggested activities.

Figure 11: Int. Material feedback

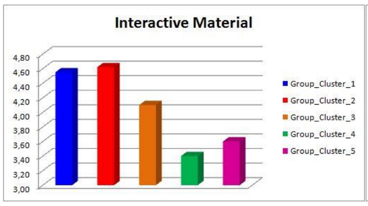


Figure 12: Video Lect. Feedback

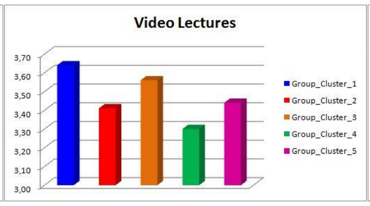


Figure 13: Self Assessment Feedback

Figure 14: Lab Exercises Feedback

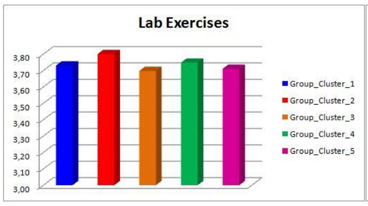


Figure 15: Lectures Feedback

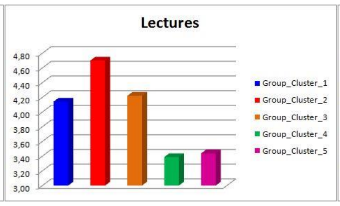
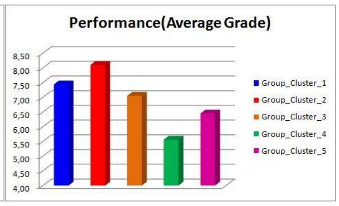


Figure 16: Final Performance



26.5 Conclusions – Future Directions

The redesign process of an e-learning course needs the evaluation of various alternatives and the decision maker needs sophisticated support and a well designed methodology. Learners' perception is central in such a process. In this paper a student centered approach was presented for redesigning e-learning courses through the analysis of students' preferential structures in the following three dimensions: (a) the dimension of students' learning behavior (b) the dimension of students' learning performance and (c) the dimension of students' feedback on the quality of the learning activities. Consistency of students' preferences with the dimensions of students' learning behavior, students' feedback, and students' final performance means to some extent successful implementation of the educational scenario. Any other inconsistency indicates a potential problem where a decision maker should analyze during the redesign process. The term "consistency" denotes a compatibility relationship between students' preferences and the other dimensions. For example, if a group with preference to Video type learning activities does not show a relative engagement in the video resources of the course may indicate a problem such as unattractiveness, not easy to use, and so on. The feedback dimension could explain some of the factors by giving more details on this specific activity. Moreover, the degree of correlation between the underlying activity and the final performance may reveal the importance (or weight) of this factor.

Our approach is based on a new method called WAP from the domain of Multicriteria Decision Making. The WAP method provides a valuable source material that includes weights of individuals' preferences that become input in a clustering process that determines (clusters) groups of preferences among students. The behavior of these groups is then analyzed in the other three dimensions. The dimension of students' learning behavior means to analyze a large volume of data captured by the underlying e-learning system. The new emerging field of Learning Analytics provides the necessary framework to answer questions related to the learning behavior of the underlying groups' preferences. Specific questionnaires could be used for the analysis of students' feedback on the quality of the learning activities. The questionnaires managed by the Quality Assurance System of each university could be used in order to capture the students' feedback and provide data for the analysis in this specific dimension. Finally, the analysis of students' performance in various graded activities as well as their final performance could give valuable feedback not only for the explanation of groups' learning behavior, but for the enhancement of the assessment instruments used as well.

The results of the initial application of our approach were presented in this paper from a real course at Piraeus University of Applied Science with promising results. Adapting education to a student-centered and personalized dimension of learning is not an easy task. Our framework gives a holistic and a fully student-centered approach to the redesign process of an e-learning system and it can be used in various levels such as a specific course, a complete curriculum or a whole educational organization.

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