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Digitally Enhanced Assessment in Virtual Learning Environments

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Abstract—**One of the main challenges in teaching and learning activities is the assessment: it allows teachers and learners to improve the future activities on the basis of the previous ones. It allows a deep analysis and understanding of the whole learning process. This is particularly difficult in virtual learning environments where a general overview is not always available. In the latest years, Learning Analytics are becoming the most popular methods to analyze the data collected in the learning environments in order to support teachers and learners in the complex process of learning. If they are properly integrated in learning activities, indeed, they can supply useful information to adapt the activities on the basis of student's needs. In this context, the paper presents a solution for the digitally enhanced assessment. Two different Learning Dashboards have been designed in order to represent the most interesting Learning Analytics aiming at providing teachers and learners with easy understandable view of learning data in virtual learning environments.**

***Keywords-** Learning Analytics; Virtual Learning Environments; Assessment; Learning Dashboard*

I. INTRODUCTION

In educational processes the formative evaluation plays a key role in effectiveness of learning since it allows the learning path to be adapted to actual student's abilities [1]–[3]. It differs from the summative assessment that aims at evaluating the educational outcomes of a specific learning path. In order to apply the formative evaluation, virtual environments supply different tools, such as quizzes, online exercises, and so on.

These are important both for students, that can self-assess the acquired knowledge, and for teachers, that could verify if her/his educational strategies are adequate to the classroom by measuring how much of the topics have been assimilated by the students. But, in e-learning contexts in order to make the formative evaluation significant it could not be limited to results of quizzes and tests. Enriching those results with data about the interactions between the users (students and teachers) and the system could be a solution. For example the level of participation to the different activities, the quality of interaction and communication among peers, could be interesting data to be used during the assessment. This perspective was also the focus of the Working Group at EDUsummIT 2011 [4], [5]. The group stated that digitally-enhanced assessment requires: 1) an authentic learning experience involving digital media with 2) embedded continuous unobtrusive measures of performance, learning and knowledge, which 3) creates a highly detailed (high resolution) data records which can be computationally analyzed and displayed so that 4) learners and teachers can immediately utilize the information to improve learning.

In this context the paper presents a solution for enhancing the formative assessment in e-learning platforms. In particular, the Learning Analytics (LAs) will be studied in order to be integrated in an e-learning platform to manage the available data. Finally, two different dashboards were designed and built to facilitate the interpretation of data using a graphical representation.

II. MOTIVATION AND PROBLEM DEFINITION

The analysis of the state of the art about the assessment allows different approaches to be classified in quantitative and qualitative methods. The quantitative approaches usually are focused on analytic measures and quantification of the student's performances to make them understandable and comparable. Often the quantitative assessment is used for the summative evaluation to measure the knowledge and skills acquired at the end of a learning path. The qualitative approaches, instead, aim at improving the learning process, while it happens, giving continuous feedbacks to promote actions and interventions to reduce the gap between the performance actually achieved by the learner and the expected performance. These types of assessment are used for the formative evaluation. The two approaches have different goals, methods and consequences but they are not necessarily at odds. Recently, however, the need to prove the effectiveness of educational institutions at different levels with evidence of the success of the educational activities has pushed the quantitative approach more than the qualitative one.

Beyond this, the assessment is a complex process: the traditional "face to face" education relies on the role of the evaluator, like a teacher or a team of teachers, who is required to carefully consider and weigh all the criteria involved in the final evaluation. In distance learning environments, the evaluator rarely has the overall picture of the learning process. Often, in fact, only quantitative evaluations, such as multiple-choice tests, are used. These are unreliable and not always significant [6], [7]. But the assessment in virtual environments presents new opportunities and challenges that should be investigated.

Research on digitally enhanced assessment is still at early stage [8]: it is necessary to understand if and how technology can support both the quantitative and the qualitative assessment. Moreover, new models of students' evaluation and assessment are requested to take full advantage of technologies [9]. As pointed out by Pachler et al. [1], indeed, the technology for assessment are not educational itself, but they can empower the educational effectiveness of assessment processes. Among the different emergent technologies the Learning Analytics have a high potential in it.

A. Learning Analytics

The Learning Analytics (LAs) represent the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs" [10].

Research in this field is becoming very popular because the digitally enhanced assessment is very pressing in virtual learning and LAs can supply the perfect tool to this end. The LA, in fact, gives methods to interpret data collected in LMSs to understand which activities involve learners and to customize the learning processes. Moreover, these data are useful also to the learners to become aware of their own knowledge and abilities in specific contexts. Thus, higher results can be achieved if students and institutions would be involved as stakeholders in the definition of learning analytics [11]. To this aim, some researches distinguish Learning Analytics (LA), Academic Analytics (AA) and the Educational Data Mining (EDM). Each of them involves different stakeholders, with distinct purposes at various levels of abstraction [12], [13]. Their common goal is to process data to find out problems and plan solutions in order to enrich the learning paths and to ensure educational success.

In particular, the EDM are useful to get value from large sets of data using data mining and machine learning methods, AA are useful to evaluate and analyze university and educational institutions from an organizational point of view [14], while LAs are addressed to analyze data in order to model social connection and learning preferences in educational settings. In this perspective, the LAs are the most suited to support the digitally enhanced assessment.

As said before, the LAs analyze mainly the user generated data, one of the main problems dealing it is the privacy. To this end, Slade and Prinsloo [11] propose to distinguish two levels of LAs data usage: the educational level and the no educational ones. The first one aims to facilitate the evaluation, reflection and personalization of curricula and it is mainly addressed to students and teachers; the second one is addressed to business analysis of the educational institutions.

Another risk in using LAs is to exceed in the quantification of activities. The LAs can be used "to track learner progress, to assist in developing and maintaining motivation, to help the definition of realistic goals and to develop plans to achieve them" [15]. But performance measurements may not be enough if they are not enriched by appropriate reflections on the learning itself.

III. Learning Analytics Process

Given the complexity of the assessment process and the inadequacy of fully automated evaluations to take into account many factors, a digitally enhanced assessment proposal has been defined. The work uses the LAs to provide teachers and learners a set of tools to simplify the assessment process and to make more significant the assessment results.

First of all, we need to identify and collect the interactions: as a matter of fact, during learning activities, students interact through the system with other people and resources. The type and intensity of the interactions vary depending on both the learning environment and the educational resources.

To this end it is important to classify the resources on the basis of their interactivity type: it is active if the content is mainly practical, such as exercise, experiment, and so on; it is explicative if the content is expositive, such as text, slides, and so forth. Moreover, it is important to classify the interactions with people (other students, teachers, tutors) that can be synchronous (through video conferences, chat, etc.) or asynchronous (using forums, wikis, mailing lists, etc.). In both cases, interactions with people and resources supplied data trails that can be analyzed and used in order to improve the learning process.

Once these data are collected and classified, Chatti et al. [16] propose a cyclic interaction where they are processed, analyzed and presented. For each new visualization, in fact, data need to be pre-processed, starting from new queries to original data, and then presented. In order to make the data significant for the formative assessment it is important to use different information visualization techniques. Visual representation of learner data, in fact, allows teacher to monitor the learner's progress and to provide her/him with more effective feedbacks than those based on quiz and test results. Furthermore the visual representation of data can be shared between teacher and learner, allowing discussion and reflection on actual data in order to improve student learning awareness.

Finally, this reflection can have impact on both the teaching/learning strategies to be adopted and the type of content to be supplied. In details, the teacher will be able to enhance the educational paths, using new teaching strategies, tools and/or teaching materials in order to adapt the training/learning process to the learners. On the learner's point of view, s/he will be aware of her/his achieved and not achieved learning goals and will be able to change her/his learning strategies according to the outcomes.

IV. Dashboard Design

To implement the described process, two dashboards have been designed for the teacher and the student.

The research on the dashboard design is still emerging but the properties proposed by Few [17] are interesting. The information in the dashboard: (1) has to support situational awareness and to promote rapid perception through the use of different visualization technologies; (2) should be presented in a way that would facilitate the decision-making process; (3) has to present, preferably in one view, the most important data that must be emphasized more than the rest.

To achieve these goals we analyzed the predictors and indicators, the learning analytics techniques and the actions and responses proposed in the literature in order to properly design our dashboards.

A. Predictors and Indicators

According to EDUCAUSE [18], three types of predictors and indicators has been identified: Dispositional Indicators, Activities and Performance Indicators, and Student's Artifacts.

Dispositional Indicators come from the information available on the student's background when s/he faces a new learning context. They are used before the beginning of the course, providing some information about his/her predisposition to learn. Many indicators are impartial and easily quantifiable (e.g. age, gender, ethnicity, grade point average, etc.); some of them are powerful predictors (e.g. the grade point average) but some research works have also included psychological measures of aptitude. Shum & Crick [19], for instance, propose the use of learning analytics to make visible the learning aptitudes and the transferable skills associated with learning in different contexts, measured on 7 dimensions (Changing and learning, Critical curiosity, Meaning Making, Creativity, Learning Relationships, Strategic Awareness, Resilience) through the questionnaire Effective Lifelong Learning Inventory (ELLI).

Activities and Performance Indicators come from the digital "breadcrumbs" left by learners during their learning activities [18]. Some of them are quantitative and are collected using monitoring systems such as logs from e-learning platform (number and frequency of logins, number of posts in a discussion forum, grades and results of quizzes). These data are relatively simple to collect and can be easily analyzed showing the results in visualization tools.

Student's Artifacts are the results of students work: essays, blog and discussion forum posts, etc. The analysis of these artifacts can provide information about the achievement of required level of experience and reasoning skills but, unlike the activities and performance indicators, they are difficult to be automatically quantified.

B. Learning Analytics Techniques

For what concerning the Learning Analytics numerous techniques have been proposed to identify meaningful patterns from the data set of the educational field. Chatti et al. [16] distinguishes them in statistics, information visualization, data mining and social network analysis.

Several Learning Management Systems (LMS) implement simple reporting tools that provide basic statistics on the interactions of the student with the system, such as total number of access, number of access per page, the distribution of access over time, posting and answering rate, percentage of read materials, etc. However, these techniques are often difficult to interpret for the LMS users.

Displaying this data in visual form can simplify their interpretation and analysis. Thanks to human visual perception skills, visual representation is often more effective than a simple flat text or data table. Various techniques for displaying information, such as graphs, scatter plot, 3D representations and maps, can be used to display information in a clear and understandable format. The most difficult task in this case is to define what representation is the most effective to the proposed target. In the learning context traditional data tables more often are replaced by graphs in order to better represent the learner performances.

Data mining techniques can be used to generate prediction and classification models from collected data, to organize them in cluster according to their similarity in order to discover association rules and interesting relationship among data.

Finally, social network analysis allows to discover the connections among users in a learning environment.

C. Actions and Responses

Based on these data and techniques it is necessary to determine which actions and responses are the most effective for both students and teachers. Indeed, students often pay very little attention (or sometimes none at all) to the tools and resources that they perceive as mechanical, impersonal and superficial; Actions and Responses generated by the LAs must be therefore properly designed.

They can be presented as fully automated responses that do not require any action from the user (such as a green/yellow/red alert), or semi-automated responses, that show significant paths in learners activities, often focusing on decreasing paths, and suggesting possible action to intervene.

V. TEACHER AND STUDENT DASHBOARDS

The model and the dashboards, were tested using data collected in Moodle LMS during a postgraduate master in "Research Manager" in the context of the National Operative Program 2007-2013 Training Plan Project of Strengthening of structures and facilities of science and technology of the Scientific and Technological Site "Magna Grecia".

The master was organized using blended settings, thus some lecturers where supplied in e-learning and some collaborative activities (using chat and forum) were organized.

A. Teacher

The teacher needs to monitor the performance of all the activities and all the students in each course. Among the leading indicators, the number of accesses has been chosen because it provides adequate information with few processing.

An overview of the access is presented to the teacher when s/he enters the dashboard, as shown in Fig.1. A linear visualization has been chosen because of time series data.

Using the mouse on the graph other details are visualized using the rollover technique, a tooltip shows the exact number of accesses in each course on a specific date, to allow comparison of numerical data.

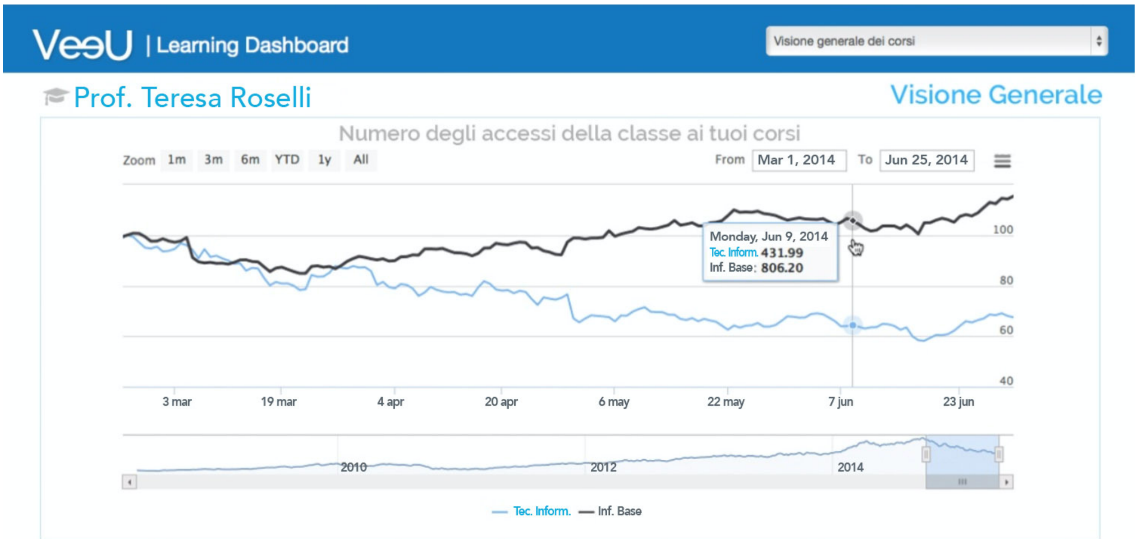

Figure 1. Number of student's access to all courses in the LMS. Different lines indicate different courses.

Also zoom and filter operations are allowed on the same graph: the teacher can zoom to set time intervals (in the top left corner) to get a periodic overview, which is more detailed than the general one. Moreover, the teacher can select a specific interval by selecting starting and ending date (in the top right corner) to identify critical events or periods.

No explicit response is presented in this case because the evaluation of the trend is up to the teacher. To provide her/him with detailed information about the kind of activities performed during her/his courses, s/he can also have access to an overview of the activities performed in the classes organized according to the kind of activity.

Also in this case s/he can filter the data, to exclude or include specific activities in the graph: for example, if the teacher is already aware of the access to educational resources of her/his class, s/he may decide to exclude this data from the graphs and to analyze the percentage of the distribution of the collaborative activities performed (chat and forum), to discover how many collaborative activities have been performed for each course.

For each course, an overall dashboard is supplied in order to find out the average of access, as shown in Fig. 2.

In this case too, it will be possible to view the graph of access of a specific student and the percentages of the performed activities, such as access to learning resources, multimedia resources, chats, quizzes etc. In addition, s/he will see the average grades and results achieved by the students.

In order to compare the class average data with each student's data, the teacher can select the student dashboard (Fig. 3) and visualize the data about student's activities, such as number of access, viewed resources and performed activities, and can visualize the resources not yet seen and missing activities. This kind of analysis allows the teacher to personalize the support of the student in the rest of the course.

Figure 2. Average students access of a specific course.

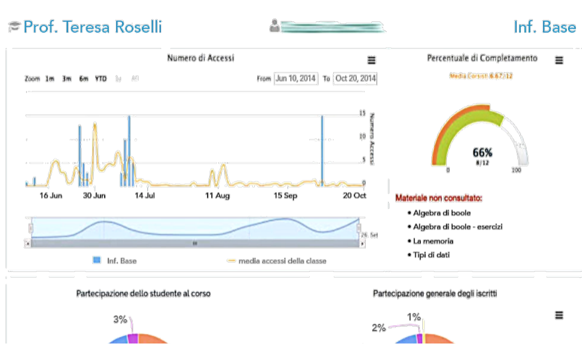

Figure 3. The student dashboard seen by the teacher (number of access, the percentage of course completition, list of resources not seen yet).

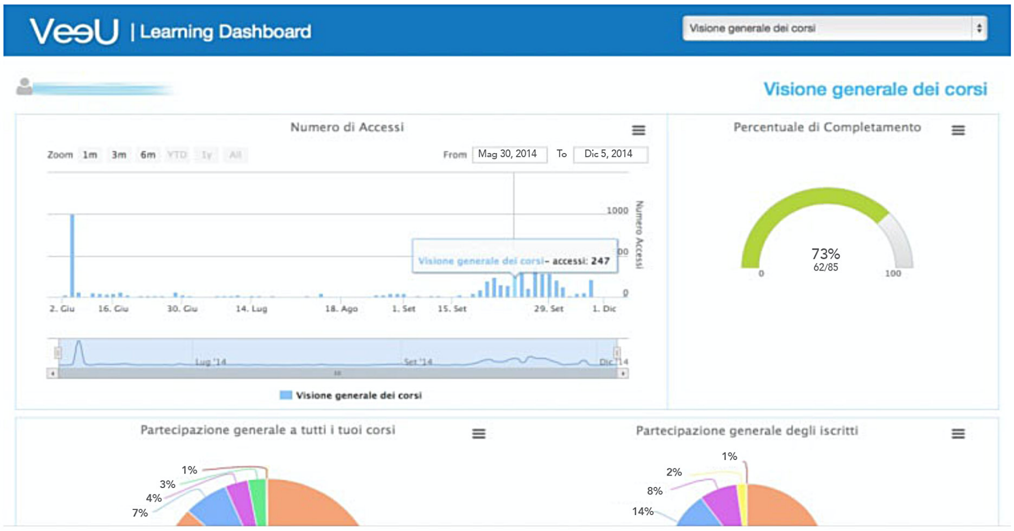

Figure 4. Main Student's Dashboard (number of access, percentage of course completition, activities graphs).

B. Student

In the learning process it is important that also the student can monitor her/his own performances in the courses in which s/he is enrolled. The main dashboard will show student's access and activities graphs. In addition, s/he will also see the completion percentage of the courses, as shown in Fig. 4.

The student, as the teacher, can zoom graphs, filter data and have more details on specific features. In addition, s/he can compare her/his own performed activities with the average activities of other members of the class. Also in this case the selection of activities will draw two pie charts that allow a comparison in real time between the student's data and the average data of the class.

For example in Fig. 5 the student can easily notice that s/he has spent a lot of effort using learning resources but s/he has not participated in the forum. Excluding the learning resources from the pie chart s/he can also notice that also her/his participation in chat activities was lower than the average of the class (Fig. 6). This kind of comparison can suggest how the student can improve her/his participation in the course to improve learning outcomes.

Note that other students' data are here presented in aggregated form to prevent privacy issues. Numerical details are available using the rollover technique.

Moreover the student will visualize her/his own test results. The spider chart has been used to allow the comparison among the results in all courses in which s/he is enrolled (Fig. 7). The graph shows a general overview of data, while data about each single test will be visible with rollover operations on it. This allows the student to have a clear vision of the learning gap (if any) to plan where and how to spend her/his learning time making the learning more effective.

To get a deeper view, the student can access the dashboard of each course through the appropriate drop-down menu in the top-right, as shown in Fig. 8.

In addition to the graph of access and the activities graph, this dashboard will provide student with the completion percentage of the course and the list of material and activities s/he has not yet completed, to promote an easy access to those resources in order to overcome her/his learning gaps.

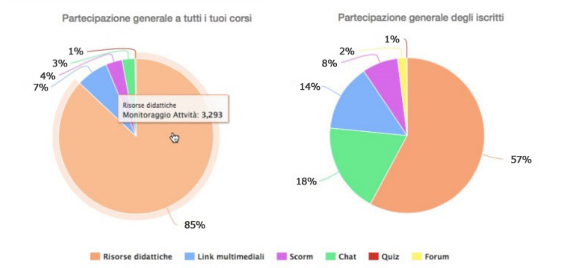

Figure 5. Student activities graph in the left side and Class activities graph in the right side (data concerns: didactic resources, multimedial links, scorm, chat, quiz, forum).

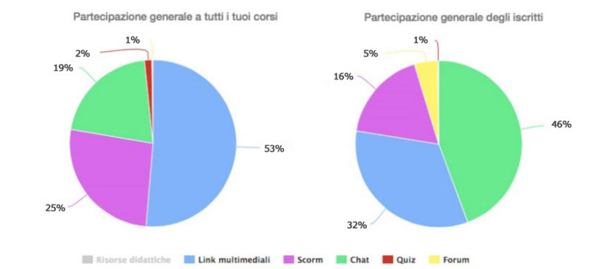

Figure 6. Student activities graph in the left side and Class activities graph in the right side where data about didactic resources has been excluded.

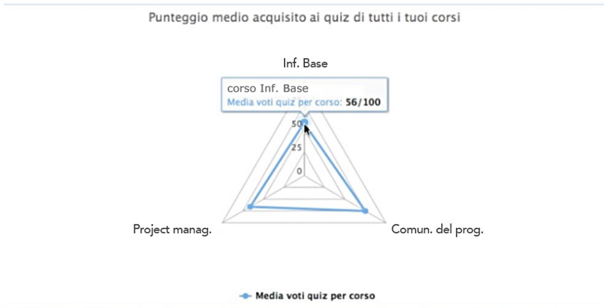

Figure 7. Spider chart displaying the avarage score obtained in the tests of all courses in which the student is enrolled.

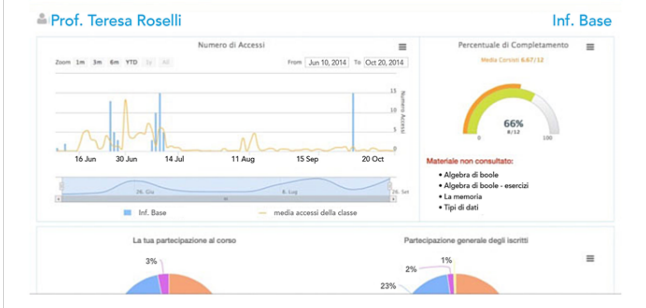

Figure 8. The student dashboard (number of access, the percentage of course completition, list of resources not seen yet).

VI. Conclusions and Future Works

To verify the accuracy and completeness of data visualized in the dashboards, an offline test was conducted using data collected by Moodle LMS during a master in “Research Manager” in the context of the National Operative Program 2007-2013 Training Plan Project of Strengthening of structures and facilities of science and technology of the Scientific and Technological Site "Magna Grecia". The learning activities of the master started in May 2014 and ended in September 2014.

For each course the students were required to access to the didactic material published in the LMS, and to participate in collaborative activities through forums and chats. The data collected during the e-learning activities allows to test that all graphs and data were well visualized in the dashboards. A deep analysis of data has to be done in order to discover relationships between the quality of student-system interaction and the students’ outcomes.

Currently, a plugin for Moodle is being developed in order to integrate the dashboards in the e-learning environment. Then a pilot study, to measure if the visualization of data enhances the student learning, will shortly be conducted.

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