

# Formative Assessment supported by Analytics Techniques: a case study on teacher and students perceptions

Alana Morais<sup>1</sup>, Danielle Medeiros<sup>1</sup>, Davide Taibi<sup>2</sup>, Ivana Marenzi<sup>3</sup>

<sup>1</sup> Universidade Federal de Campina Grande, 58429-900 Campina Grande-PB, Brazil  
{alanamorais, daniellemedeiros}@copin.ufcg.edu.br

<sup>2</sup> Consiglio Nazionale delle Ricerche, Istituto per le Tecnologie Didattiche, Palermo, Italy  
{davide.taibi}@itd.cnr.it

<sup>3</sup> L3S Research Center, Hannover, Germany  
{marenzi}@L3S.de

**Abstract.** This article aims to compare the teacher and students' perceptions on the formative assessment process carried out in a blended course in Brazil. To achieve this goal, the authors used analytics techniques to analyse the online activities which were supported by the LearnWeb collaborative platform. The performed analysis investigated metrics related to the interactive student profile considering learning activities such as: creating groups of resources, selecting, uploading and commenting on learning resources. The results show that clustering and classification techniques may be used to investigate students profile and can be useful in preventing students' dropout. The authors conducted a survey to draw an analogy between users' opinions about the course and their behaviour on the platform. The questionnaires results highlighted the positive impressions, awareness, and motivation of the teacher and of the students during the formative assessment process.

## 1 Introduction

In the last few years, analytics had a huge impact in different fields. With respect to the educational sphere, the research fields of Educational Data Mining (EDM) and Learning Analytics (LA) have studied the effects of applying analytics techniques to the analysis of educational data. Even though the two fields overlap in several aspects [1], there are relevant differences that make complementary the approaches adopted by the two communities. The differences and similarities between the two communities led to a debate [2]. A very concise distinction is: LA gives more emphasis on creating procedure to support human judgment regarding the learning progress, while EDM is more focused on creating models to support automated processes in intelligent tutor systems.

In our work we have adopted a mixed approach to support formative assessment processes in a blended course. LA techniques have been adopted during the course to monitor students' engagement and provide teachers with tools to promptly intervene. EDM approaches have been applied at the end of the course to analyze and report the

overall learning experiences of the students in order to evaluate course progress based on evidences supported by data and to obtain useful insights to facilitate the design of future editions of the course.

The work was led by the following research question: *What are the teacher and learners perceptions about formative assessment outcomes in a Brazilian blended course using the LearnWeb collaborative platform?*

Our goal was to better understand how the main actors of the teaching-learning process perceive formative assessment informed by an EDM approach. For this purpose, a case study was conducted over a period of eight weeks of a blended course in Computer Science. During the course we applied Learning Analytics techniques to support formative assessment: teacher used the LearnWeb Formative Assessment Module to monitor students' engagement (Section 3). After the course, we performed EDM on the online activity logs, and collected two questionnaires to draw an analogy between users' opinions about the course and their behavior on the platform (Section 4). On the one hand, we investigated students' perception about the learning activities and the interaction in the online collaborative platform. On the other hand, we investigated to what extent formative assessment outcomes (supported by visualization and evaluation tools) were perceived as informative and efficient by the teacher.

In the remaining of the paper we provide an overview on related work (Section 2) and a description of the LearnWeb, the platform adopted to support the learning activities and to carry out formative assessment (Section 3). In Section 4, we describe the research phases in this study, and in Section 5 we analyze and discuss the results.

## **2 Background overview**

In the last few years, Learning Analytics (LA) emerged as a research field with the aim of collecting and analysing learners' traces for a better understanding of the learning experiences [3].

In online and blended courses, collaborative environments are often used as data sources for analytic tools, in order to extract meaningful information about the students' specific needs. The most common analytic technique used for this purpose is Data Mining (DM). This occurs both by the popularization of Educational Data Mining (EDM) approaches in recent studies [4] and by the large amount of data generated during these courses, which turns manually processing of this data an impractical activity to be executed by the instructor without the help of learning analytics tools [5].

Through Learning Analytics techniques, students' logs are visualized by teachers to find out relevant hints about students' interactions within the online learning system. The analysis of quantitative data related, for example, to students' access to learning content, or to students' participation in online learning forum, can be leveraged to detect students' engagement and promptly intervene to sort out at-risk situations, such as early dropout [6].

Learning Analytics techniques have been also successfully adopted to support formative assessment practices. For instance, Taibi and colleagues [7] applied a

backwards stepwise regression model to infer the relationship between the students' interactions within the platform and their learning performance.

Learning assessment of students' knowledge acquisition is one of the major concerns of the teaching-learning process. In educational settings, performance assessment strategies are used with the purpose of analyzing and evaluating learners' understanding of the topics discussed throughout a course. Whereas in summative assessment mainly the final outcome is evaluated, the objective of formative assessments is to provide feedback to students rather than to evaluate them to assign course grades [8].

In online learning activities, students' traces play a key role to support the formative assessment process. Activity logs of the online e-learning system can be taken into account and analysed to obtain relevant insights on students' engagement in general, and students' learning behavior in particular. The feedback received during the formative assessment process facilitates learning, assists students in reflecting on their learning and revise their misconceptions, and improves their motivation [9,10,11]. Formative assessment techniques provide insightful feedback that help to guide and shape the learning process during instruction [12]. Furthermore, they provide teachers with opportunities to monitor students' progress and their learning curve along the course, and to adjust the teaching strategies accordingly [13].

This scenario is often observed in the e-learning context, where monitoring the learner's progress is usually an essential part of the learning process, since students' retention and limitation of the dropout rates are important factors for a course success [14]. Therefore, formative assessment can offer effective solutions for identifying and dealing with potential dropouts.

In blended learning scenarios, traditional performance indicators based on outcomes-centric analytics considering learners' performance on predefined tasks are not enough to evaluate the learning process. The focus has to shift from what the learner can achieve individually, to a more participatory perspective where students learn from the interaction with their peers [15].

Social Learning Analytics has been defined by Shum and Ferguson [15] as "a distinctive subset of learning analytics that draws on the substantial body of work demonstrating that new skills and ideas are not solely individual achievements, but are developed, carried forward, and passed on through interaction and collaboration". Social learning has emerged as a significant phenomenon and it is characterized by the involvement of learners in social activities in which students learn from others interacting with their peers [16]. In this scenario, the evaluation of learning achievements requires specific tools. Shum and Ferguson [15] identified five categories of analytics in relation to online social learning. In particular, the authors distinguished between inherently social analytics, that can be developed in collective contexts, and socialised analytics, that have been initially developed to analyse personal learning activities, but that have specific characteristics in collective context.

In general, Social Learning Analytics techniques and tools can be leveraged to identify disconnected students as well as students playing the role of information hub. In addition, they are relevant to identify patterns of communication exchange in students network and to reveal the structure of learners' communities.

In our experimentation, data mining techniques have been adopted to support formative assessment practices focused on the analysis of social processes that take

place during learning. Clustering algorithms have been applied with the aim of evaluating students' engagement in social learning activities. Furthermore, the feedback provided by the algorithms have been analysed by the teacher in order to support a promptly intervention aimed at reducing students' dropout.

### **3 Learning scenario and methodology**

The context of the case study was a blended course in Logic in Computer Science which took place at the Universidade Estadual da Paraíba, in Brazil, spanning over a period of two months (eight weeks) from February 2016 to April 2016.

The participants were 35 students, aged between 16 and 25, of which nearly 70% were male. Their mother tongue was Portuguese and the course was designed in Portuguese. Almost 69% of the students had never interacted within a Virtual Learning Environment before. The participants were informed about the scope of the case study, but they did not know how and when formative assessment would happen during the course.

Four distinct collaborative assignments were carried out as described in the Table 2 (section 4.1), using the LearnWeb environment. Each assignment was evaluated by the instructor, based on direct assessment of student individual and group performance throughout the course. The assignments were planned by the teacher and one technician in order to promote a collaborative dynamic between students, where all functionalities offered by the LearnWeb environment would be used at the same time.

#### **3.1 LearnWeb as a Formative Assessment tool**

LearnWeb is a learning and competence development environment, which allows users to share and collaboratively work on resources collected from the web or user-generated [17]. It provides users with a search interface for resource discovery and sharing across various Web 2.0 services such as YouTube, Flickr, and Slideshare, including LearnWeb itself, and offers a Personal Learning Space. In order to support collaborative searching, LearnWeb provides automatic resource annotation; resources in LearnWeb can be bookmarked, tagged, rated, and discussed by all users who are allowed to access them. Comments on particular learning resources can be used to enrich the description. Users can create folders to bundle resources that belong to the same learning context. Hence, the LearnWeb community can collaboratively identify the best learning resources for specific learning domains. A discussion of the full potentialities and affordances of LearnWeb as a collaborative platform is beyond the scope of this paper, but can be found in a series of published studies [17, 18].

The present study focuses in particular on the use of the Formative Assessment Module and on the analysis of the potentialities to support the learning process.

### 3.1.1 The LearnWeb Formative Assessment Module

The Formative Assessment Module in LearnWeb aims to support both the teacher and the learners, increasing students' achievement. Learners need to know: the learning target, where they are positioned in regards to the learning target, and what they can do to close the gap. The LearnWeb Formative Assessment Module provides students with clear learning targets, examples and models of strong and weak work, regular descriptive feedback, and the ability to self-assess, track learning, and set goals. Furthermore, the Formative Assessment Module allows a visual analysis from the virtual classroom to the teacher. In order to address the needs of different scenarios the LearnWeb Formative Assessment Module was designed from four main perspectives:

- A course perspective, where the teacher has an overview of a specific course and can make comparisons between classes (Fig. 1).
- A class perspective, where the teacher can monitor and compare the activities of small student groups within the same class. This view can be shared with each workgroup to raise awareness concerning the activities carried out by other group members and increase motivation and competitiveness between groups (Fig. 2).
- A personal perspective, where the teacher can visualize information about a specific student (Fig. 3).
- A user group perspective, where the teacher can visualize his/her class in groups (clusters) according to the student interactive profile. This view shows the most participative students in the same group according to their interactions on the platform (Fig. 4).

All perspectives provide to the teacher the possibility to send a feedback message and generate three different types of chart (i.e. bars, line and pie chart). The teacher's target can be the class, groups in the courses, specific student or the cluster of students identified by the LearnWeb Formative Assessment Module. This module supports formative assessment practices by allowing teachers to interact with students in order to provide prompt intervention when critical situation or at risk conditions have been identified.

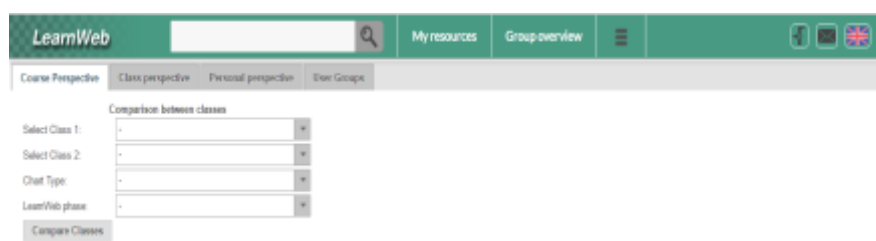
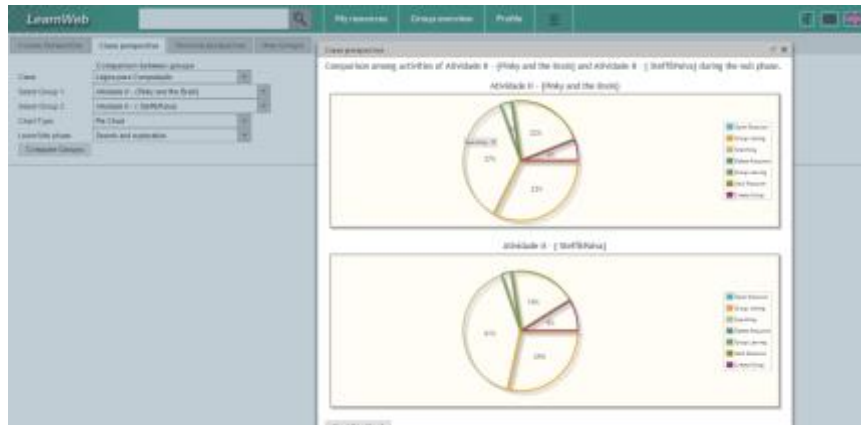


Fig. 1. Formative Assessment Module in the LearnWeb

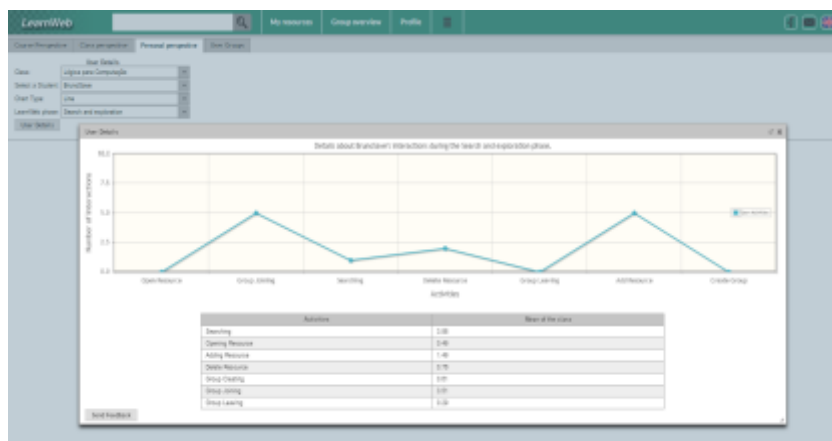
Regarding the student group functionality, a useful analysis carried out by the teacher was the comparison between groups during the course. The groups comparison allowed the teacher to understand students behavior in groups according to different learning approaches. The class perspective (Fig. 2) visualized by the teacher during the Assignment 2 shows two different groups: “Atividade II - {Pinky and the Brain}” and “Atividade II - {Steff&Paiva}”. In this case, the teacher noticed a

similar behaviour between the students groups regarding the use of LearnWeb functionalities. However, the level of searching and adding resources in both groups was lower than the teacher expectations. Based on this information, the teacher provided feedback messages to adjust the unexpected behavior, encouraging students to increase searching and uploading. Sometimes the teacher needed a more precise overview about the personal interactions of specific students in the group.



**Fig. 2.** Class perspective analysis

In such cases, the teacher explored the Personal Perspective view in the LearnWeb Formative Assessment Module. This information helped the teacher to plan corrective feedback and ad-hoc advices. Fig. 3 exemplifies a user profile. The visualization confirmed the low rates of searching activity and, consequently suggested the need to monitor the student behavior and act to solve some user learning mistakes.



**Fig. 3.** Personal Perspective Analysis

Finally, the LearnWeb Formative Assessment Module provides the user groups analysis. In this perspective, the teacher can visualise his/her class in groups (clusters)

according to the student interactive profile. The ultimate goal is to allow the teacher to get a better understanding of the classroom dynamics. Fig. 4 shows a visualization which helps the teacher identify less-active students (for example, student 10 and 11 in cluster 3) and encourage them to participate more in the online interactions, according to the user interactions in the course (it was based on specific variables as reported in Table 1). When the clusters are generated, the teacher can visualize additional information in the clusters charts built by the Formative Assessment Module.

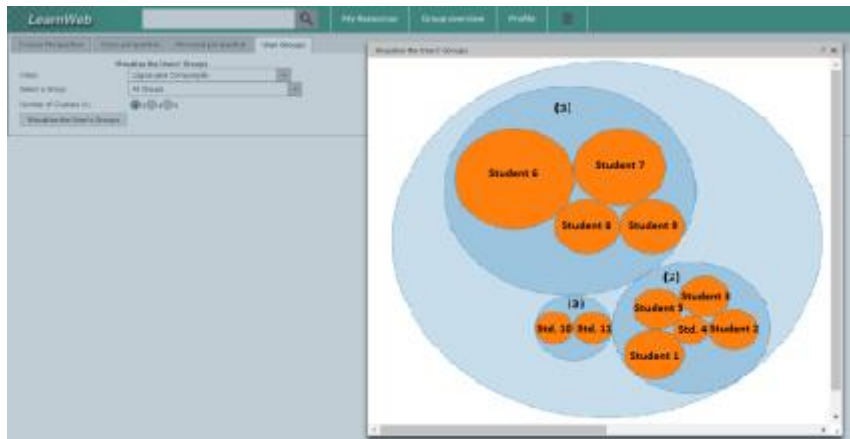


Fig. 4. User groups analysis

Table 1. Selected user variables in each log record.

Variable	Variable Description
Resource Tagging	Number of tags added by a user
Comment	Number of comments created by a user
Group Joining	Number of times that a user joined in a group -
Group Leaving	Number of times that a user left a group
Resource Opening	Number of times that a user opened a resource
Downloading	Number of times that a user downloaded a resource
Searching	Number of times that a user performed a search
Resource Deleting	Number of times that a user deleted a resource
Resource Edition	Number of times that a user edited a resource
Resource Addition	Number of times that a user added a resource
Group Creation	Number of times that a student created a group
Comment Deleting	Number of times that a student removed a comment

For example, (i) it is easy to detect which student belongs to which group because the Student ID is visualized inside each circle (see orange circles in Fig. 4), (ii) it is possible to get details about students interactions when the mouse cursor is over the student name in the chart, and (iii) the size of the circle radius represents the participation level of a student (according to the variables described above) until the moment when the analysis was done. The radius function was defined in Phase 1 (course design) of this process and it involves four main student variable sets:

- a) s1: Number of comments, resource addition (uploading), resource tagging, and group creation;
- b) s2: Number of searching, resource editing, and resource opening;
- c) s3: Number of downloading, group joining, and resource deleting;
- d) s4: Number of comment deleting, and group leaving.

The participation level (P) function is a weighted arithmetic mean of those students' variable sets. The weight of each variable sets was defined by the teacher and the technician in Phase 1, but the construction of charts using this metric happened in the second phase. The set s1 is the most relevant for the teacher and contributes more than anything else in calculating the mean P. This happens because the targets in the course guided the teacher to explore comments, adding resources, tagging resources, and creating groups as the most essential functionalities during the course. For that reason the weight w1, related to the s1 variable is set to 4 and the other weights (w2, w3 and w4) are set to 2:

$$P = (w1*s1 + w2*s2 + w3*s3 + w4*s4) / w; \text{ where } w1=4, w2=2, w3=2, \text{ and } w4= 2$$

As a result of this phase, the clusters charts support the formative assessment process. In our scenario, the teacher decided to investigate three main student groups after some tests carried out during the first week of the course.

## 4 Research Phases

In order to investigate the efficacy of the formative assessment approach, and compare it to the users' perceptions, we divided the specific learning scenario in four phases and analyzed each of them. Fig. 5 presents the sequence of the four phases which are: (i) Course Design, (ii) Course delivery, (iii) Questionnaires and Classification analysis, and (iv) Final analysis.

The following sections describes the actions, techniques and tools which were used in order to analyse each phase of the study. The actual discussion of the results is presented in Section 5.

### 4.1 Phase 1 - Course Design

Before the beginning of the course, the teacher planned, scheduled, reviewed and tested all activities, while the technician supported the teacher on technical issues.

It was decided to adopt a blended format for the course. Blended learning is an instructional model that combines teaching methods from both face-to-face and online learning. It can be implemented in a variety of ways, ranging from models in which curriculum is fully online with face-to-face interaction, to models in which face-to-face classroom instruction is integrated with online components that extend learning beyond the classroom or school day. In blended learning scenarios, teachers can use various types of technology to offer countless different learning pathways to students, to provide an integrated learning experience. The advantages of using an online



platform in blended learning environments are not only related to the functionalities it provides to support students' learning activities, but also to the opportunity for teachers to evaluate students' work throughout their learning pathway.

Blended learning brings about an important shift in formal education, making the teaching/learning pathways much more flexible: students can collaborate both in class and online, they can organize the learning activities with a different time schedule, their role and engagement in the learning activities can change due to the use of technology. Such flexibility increases the need for formative assessment, which can help monitor student progress and then inform the choice of pathway forward.

This phase took into account the design of the students' activities and assessments, the period in which the activities were carried out, the feedback strategies adopted by the teacher, as well as the students' evaluation for each activity. The outcome of this phase is a document that describes all activities and the assessment approaches which were implemented in the course (see Table 2).

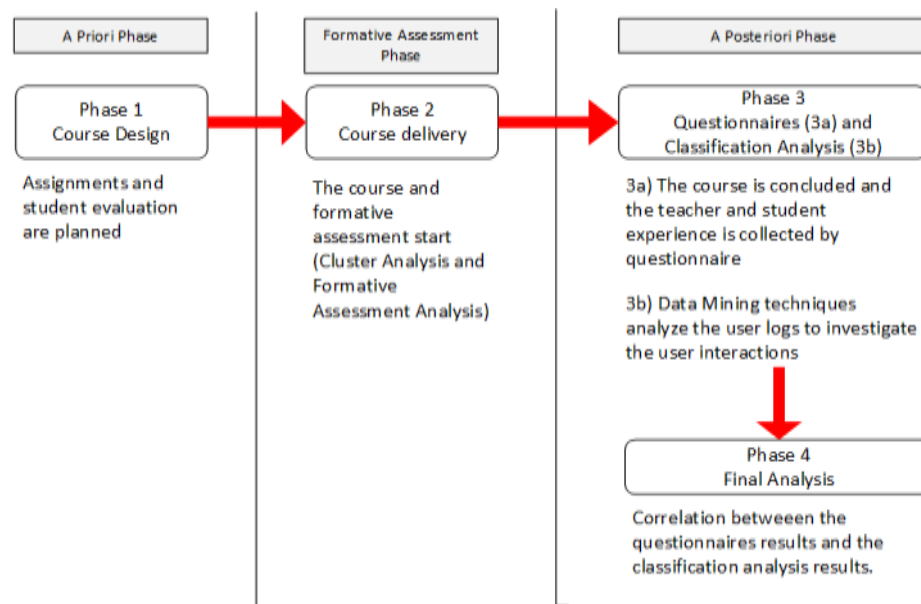


Fig. 5. Phases Sequence in the current study case

Table 2. Assignments proposed in the Brazilian course

Assignments	Description	Duration	LearnWeb Functionalities
1 Resource Sharing	The main idea of this assignment was to share information, by means of sharing learning materials. After creating a group of resources, each student had to search and upload one or more learning resources related to the topic Logic in Computer Science. Students could	Week #1 to Week #8	questionnaire perception about the formative assessment process

	also exchange ideas and opinions through comments.		
2 Resource Annotation and Discussion	This assignment aimed at improving learner's knowledge about Propositional Logic, by creating and discussing practical logic problems. The students, organized in teams of two individuals, had to create a group of resources to exchange ideas about the present topic of discussion and elaborate their own logic problem to be solved by other teams. The teams could use the group forum to debate about strategies and use the comments section to discuss about uploaded materials. At the end of the assignment, the students had to create a Google Document with the logic problem formulated by them.	Week #2 to Week #4	Students groups
3 Team challenge	This assignment is complementary to the previous one. After the completion of the second assignment, the previously formed teams had to challenge each other by exchanging the logic problem created by them. The challenging team could add comments or other resources with hints to help the challenged team, if they thought it was necessary.	Week #5	Students groups
4 Final Evaluation	The objective of this assignment for the students was to practice all knowledge acquired throughout the course. A specific group was created for this activity, where the teacher uploaded a set of logic problems and the students had to choose a distinct problem to solve. At the end, the students added their solutions in the activity group and discussed them with the others through comments.	Week #6 to Week #8	Discussion Forum and Google Document

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## 4.2 Phase 2 - Course Delivery

In this phase, the LearnWeb Formative Assessment Module (section 3.1) was used by the teacher to provide timely feedback to student outcomes. During the course, the teacher carried out the data analysis from three different perspectives: by Class, User Personal perspective and Group perspective. During this phase the learning materials were delivered and the researchers, the teacher and the technician, started to monitor the students' activities. After the enrollment, students worked on the learning activities, while the teacher monitored their performance applying formative assessment strategies. From the technical point of view, cluster analysis was used to define a profile for each student according to their behavior online. The cluster analysis was supported by the group perspective functionality (Fig. 4) in the LearnWeb Formative Assessment Module and was based on specific variables as reported in Table 1.

### **4.3 Phase 3 - Questionnaires and Classification Analysis**

The third phase consisted of two complementary tasks: user questionnaires and data classification analysis. Both of them started after the course was concluded (a posteriori analysis).

#### **a) Questionnaires**

The questionnaire is a basic tool, not only for measuring individual perceptions about a phenomenon, but for assessing users' experiences during the course. The main aim of the questionnaires analysis was to investigate the teacher's opinion and the students' opinion about the formative assessment process adopted in the course. The teacher designed the questions for students in collaboration with the technician, and the technician designed the questions to be asked to the teacher.

Both questionnaires were designed so that answers were scored, and scores were summed up, to obtain an overall measure of the attitudes and opinions of the teacher and of the students, who answered the questionnaire on voluntary basis. One advantage of using questionnaires is that respondents have more time to consider their responses carefully without interference by the investigators. Our questionnaires included two types of questions: open-ended and closed-ended. An example of a multiple choice question is "Which one of the functionalities below would you judge to be relevant to support the activities in your group? (Add resource, Add Tag, Search, Comment, Change the privacy settings, Forum, Download of resources)". While the students were questioned about their study motivation and routine using the LearnWeb and the usefulness of the functionalities provided by it, the teacher answered questions about her expectation, in the beginning of the study, and her impressions about the formative assessment after using LearnWeb as a teaching tool (more details on the questionnaires results are given in section 5.2).

#### **b) Classification Analysis**

The second step in the third phase is the students' classification analysis according to their behavior in the course. Some tests involving decision tree techniques were executed in order to support the teacher in better understanding a multiple variable analysis in the Brazilian course. The classification analysis focused on correlating the user variables listed in Table 1, with the dropout status (more details on the classification results can be found in section 5.3).

### **4.4 Phase 4 - Final Analysis**

At this stage, we executed the final analysis of the case study after reviewing the results obtained over the previous phases. Other observable variables were also taken into consideration for the analysis concluded in this phase, such as the total of completed assignments of the students and dropout rates in the course.

## **5 Discussion of the Results**

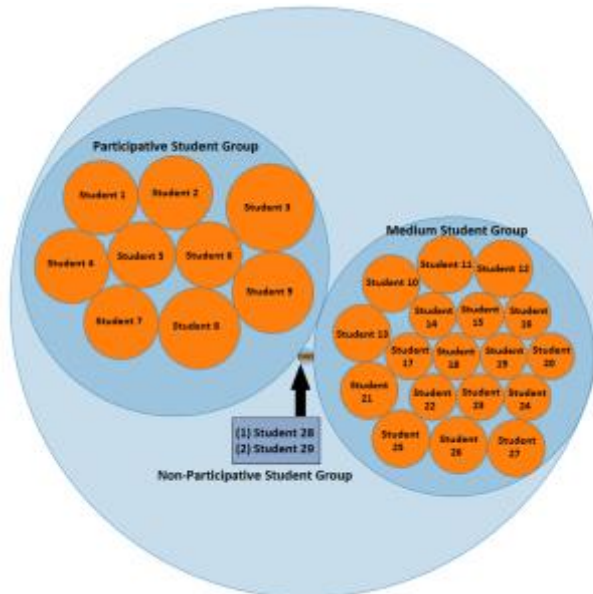
On the basis of the methodology and of our research question, in this section we organize and comment about the main results in our study. The analysis was performed in two different moments: at the end of the second week and at the end of the sixth week.

### **5.1 Phase 2 results - Clustering results**

As we mentioned in section 3.1, the Formative Assessment Module uses the K-Means algorithm to identify the clusters according to the students interactions captured in the log files in specific periods during the course. Through the K-Means algorithm, three main groups were obtained based on metrics related to the students' interactions (Fig. 4).

Every week, the teacher monitored the clustering results in order to identify the most appropriate variables to delineate the interactive student profile. According to the characteristics of each group, the teacher suggested to call them "Participative Student Group", "Medium Student Group" and "Non-Participative Student Group". A detailed analysis of the features of each group was carried out at the end of the second week and at the end of the eighth week.

The first round of analysis took into account the activities performed after the second week, related to Assignments 1 and 2. The resulting groups formed a scenario composed by a numerous "Medium Student Group" and two other groups: "Participative Student Group" and "Non-Participative Student Group" (Fig. 6). The smallest group in Brazilian scenario was the "Non-Participative Student Group, composed by two students.



**Fig. 6.** Clusters built in the second week

In the Brazilian course, students belonging to the “Medium Student Group” typically missed some deadlines, did not solve Assignment 1 or Assignment 2, and opened some resources. The “Participative Student Group” included students who did the assignments, opened some resources, and answered some colleagues. Finally, the “Non-Participative Student Group” represented students who accessed the environment only to enroll in the course. The teacher made an effort to provide some feedback messages and review activities to motivate the class throughout the course. During the student interaction in each assignment, the teacher sent out messages of encouragement or warnings about close deadlines to specific groups of students. For example, for the “Non-participating Student Group”, the teacher periodically sent out motivational messages and tips about learning resources and assignments.

The second round of analysis took into account the activities carried out during the eighth week, related to Assignment 4. Fig. 7 shows that the “Participative Student Group” increased in comparison to the second week, since it is possible to identify a group with an increased number of circles and with a larger diameter.



Fig. 7. Clusters built in the eighth week

The cluster named “Non-Participative Student Group” presented a modification related to its members. After the second round of analysis, two members belonged to the mentioned cluster, they were: Student 28 and Student 29. However, after the eighth week, this group changed and it was composed by Student 21 and 29. Two main reasons can be highlight to the reformulation of clusters between the second and eighth round of analysis:

- (i) After the second week, the teacher provided an extra support to motivate the members of the “Non-Participative Student Group” with some feedback messages; this motivated Student 28 to review his interactions and to improve his performance in the course.
- (ii) Student 21 lost his access login to LearnWeb and gave up interacting weekly when the course advanced, regardless of the teacher feedback.

Some cluster reformulations were expected during the analysis as a natural consequence of the periodic interventions of the teacher, of the students’ motivation feeling, and of their interactions throughout the course.

If the study was interrupted at this stage of the analysis, it would not have provided indicators to understand other behaviors. For example, the behaviors that may be associated with students belonging to the group “Participative Student Group” and “Medium Student Group”. Thus, the importance of continuing the analysis according to the methodology presented in Section 4.

## **5.2 Phase 3a - Questionnaire results**

After analyzing the students groups during the course delivery (Phase 2), we investigated the teacher and students opinion about the formative assessment approach adopted in the course. Questionnaires proved to be a quick and efficient way of obtaining information from the participants to the virtual classroom. Both questionnaires (for the teacher and for the students) were delivered at the same time after the end of the course.

### **a) Teacher Questionnaire**

The questionnaire about teacher's perceptions investigated four main aspects: (i) the teacher's assumptions about the formative assessment process, (ii) the overview about students interactions in the course, (iii) the teacher's satisfaction, and (iv) the teacher's motivation. This phase aimed to investigate whether the teacher understood the classroom needs and explored properly the environment to support them.

Initially, the teacher said that she was excited to involve her classroom in this experience, and to monitor students' activities since the beginning of the semester. According to her answers, the formative assessment approach worked as planned. It allowed her to re-think and to adjust some assignments according to the classroom needs. This aspect was fundamental to motivate and decrease the level of students' dropout in the course.

Even though the teacher was satisfied about the formative assessment analysis, she would like to investigate the results further in order to understand some specific student's behaviors that remain unclear. For example, what are the functionalities more used for the students in the course?

### **b) Student Questionnaire**

The second questionnaire focused on the students' perceptions on the course and on their opinions about the formative assessment process. The proposed questions explored four main aspects: (i) the student's routine during the course, (ii) the student's motivation, (iii) the risk of student's dropout in the course, and (iv) their overview about the course. These aspects guided the authors to understand the students' awareness and acceptance of the formative assessment process.

First of all, the questionnaire analyzed the students routine in the learning process. The study identified an interactional profile during the course. Most users accessed the environment from 1 to 3 times per week, 73% of the students tried to solve all assignments, and they interacted with the virtual environment at home and at school.

Regarding the students motivation, 54% of them affirmed to be motivated (Motivated or Very Motivated) during the assignments. The most popular activities were Adding resource, Download resource, and Creation of group.

Concerning the students' dropout, one of the questions asked the students to "Assess the risk of dropout of the activities through the course". As a result, 46% of the interviewees affirmed to think about it, due to the difficulties faced during the learning process.

The importance of the course feedback was highlighted by students in the questionnaire. One student commented: "The assignments were moderate in difficulty, productive and practical. I was very motivated to solve all the [logic]

challenges. However, I had some issues because I did not have sufficient knowledge of the theory at the time when the assignments were performed”. When the teacher identifies this kind of issue, he/she can provide feedbacks to provide extra materials, solve questions, and support the learning process. Besides that, the questionnaire also showed that the students were somewhat motivated to use the platform during the experiment.

### 5.3 Phase 3b - Classification results

The Classification Analysis (Phase 3) is useful to answer unsolved questions in the course. For example, the Brazilian teacher wanted to understand better the link between the students profile and the students’ dropout status in the course. The dropout status is a metric related to the final situation of the students in the course (“dropout” or “non-dropout”). Despite the teacher’s efforts to motivate the class during the course, dropout rates reached a percentage of 46% at the end of the course.

Several classification techniques were performed during this phase; among them the decision trees provide the most interesting feedbacks for the specific scenario. The decision tree is useful to create a model that predicts the value of a target variable (dropout status) based on several input student’s variables (listed in the Table 1) [19]. It is important to emphasize that the group analysis did not influence the investigation at this stage. In our study we applied the following algorithms: J48, NBTree, Random Tree, ADTree and RepTree. Table 3 lists the parameters used for the comparative analysis. All techniques were implemented using the Weka suite.

**Table 3.** Classification techniques

Tree	Correctly Classified Instances	Incorrectly Classified Instances	ROC Area
REPTree	76.92 %	23.08 %	0.85
Random Tree	92.31 %	7.69 %	0.95
NBTree	69.23 %	30.77 %	0.90
ADTree	92.31 %	7.69 %	0.98
J48	92.31 %	7.69 %	0.95

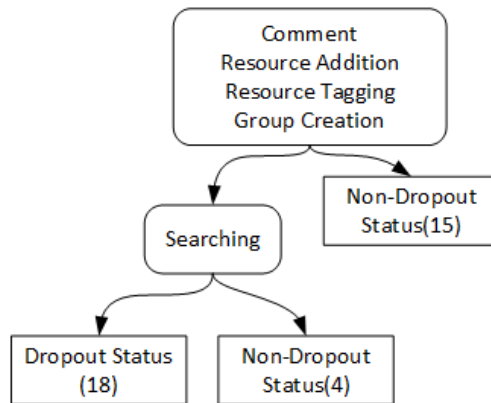
According to the results obtained, most of the algorithms are able to classify correctly a part of the sample and provided good results. The only exception is the NBTree tree that classified less than 70% of the sample instances correctly. The ROC rate of all trees were constructed from a point of view on what can be demonstrated in other classification techniques.

Several sorting rounds were performed using as individual metrics and grouped to extract non trivial information. The trees normally present squares to represent the node that corresponds to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf (rectangles) represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.

When interpreting the built decision trees, some findings were obtained. For example, during an analysis of the J48 tree it was identified a link between the dropout status and the students that did not comment, did not add resources, did not



add tag, did not create groups and did not execute resources, and search in LearnWeb (Fig. 8). Moreover, the trees built using the ADTree and Random Tree algorithms confirmed the link between the dropout status and some functionalities. However, the REPTree algorithm (Fig. 9) identified a relationship among the students dropout status, searching, and resource addition.



**Fig. 8.** J48 Tree (week 8)

Other user variables highlighted by the classifications mentioned above were not important for this algorithm. Such information can be useful for the teacher during the final course assessment, facilitating the review of the pedagogical strategies adopted during the course, and providing additional knowledge to improve the next classes.

When we compared the students' and the teacher's opinions, we found different views about the usefulness of the functionalities in the course. The teacher believed that the most useful functionalities are searching, resource downloading, sending feedback messages, and resource addition. While most of the students cited as the most interesting functionalities resource addition, group creation, and resource downloading. Regarding the formative assessment process, the teacher highlighted as the most useful functionalities (i) the possibility to send feedback messages to students, and (ii) the possibility to visualize personalized charts to identify any students fail status.

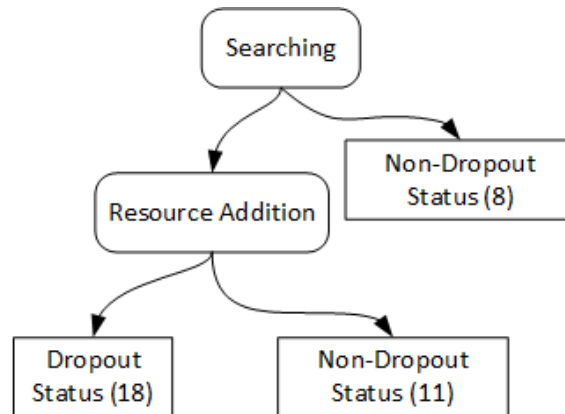


Fig. 9. RepTree (week 8)

#### 5.4 Phase 4 - Final Analysis

In order to provide an overview of the whole process carried out in this research, we take into account the EDM results presented by the clustering charts (Section 5.1) and the classification analysis (Section 5.3), as well as the subjective view presented by the students and the teacher through the answers to the questionnaires (Section 5.2). Throughout the execution of all the phases of this research, the teacher analyzed the results obtained in order to extract information that would be useful to help improve the pedagogical practices used for the case study.

Before the start of the course, the teacher intended to use the Formative Assessment functionalities available in LearnWeb as a motivation factor to carry out more dynamic activities and instigate students to better learn the content discussed in the classroom, as well as to encourage them to interact more with their colleagues.

Overall, the students were motivated to use the platform to complete the assignments. Only three students claimed that they didn't feel motivated to use the LearnWeb environment and completed 100% of the proposed assignments.

Despite these facts, the teacher pointed out that the behavior of the class throughout the course was quite heterogeneous. This was clear while observing students' behavior illustrated by the clustering analysis. A few students threatened to give up interacting with the platform from the beginning of the course; while others struggled to understand how LearnWeb works or they found the course content difficult to understand. More than 76% of the students were very motivated to carry out the activities and finalize them on time. Some behavior of the less active students can be explained by the fact that more than a half of them had never used a collaborative platform before. The teacher mentioned that some of the students were not attracted to participate in the environment, preferring to discuss some aspects of the assignments face-to-face rather than commenting or using the online forum.

As mentioned before, while understanding students behavior, the instructor worked on motivating the non-participative students to interact and participate more in the assignments. In this respect, the teacher described the LearnWeb Formative Assessment Module as an “interesting tool that can offer the educator the opportunity

to review and analyze the student's' profile throughout the course, offering the opportunity for changes to be made in the learning practices and methodologies in order to be more effective”.

In addition to this, the final results show that almost all students considered the use of the formative assessment during the course as a positive experience and about 75% of them would recommend the use of a virtual environment to support learning.

## 6 Conclusions and Future Work

In this paper, we presented an overview about teacher and students perception on the Formative Assessment process. This methodology allowed understanding student patterns and answering teacher issues during the formative assessment process. The aim of this research extends beyond demonstrating the practical importance of the learning analytics infrastructure in the formative assessment process. Additionally, the main contribution of this study was to take into account the user perception about the full process. The outcomes of this study contributed to a better understanding of students' interpretation of feedback and the impact that this had on their motivation and goals.

Regarding the initial question of our research (*What are the teacher and learners perceptions about formative assessment outcomes in a Brazilian blended course using the LearnWeb collaborative platform?*), we collected and analysed the interest, motivation and engagement of the students and of the teacher during the learning process. Students' scores improved, even though technical difficulties could not be ignored during this process.

For this reason, we intend to improve the LearnWeb Formative Assessment Module including better charts, temporal analysis, and supporting students self-assessment during the course to address one of the students requests highlighted in the questionnaire as mentioned in section 5.

In general, the formative assessment process was a successful experience in the Brazilian course because there was an improvement in the class performance and the dropout score rate was affected directly by the student motivation. Students reported their impressions about this aspect in the questionnaire, as: “The LearnWeb platform was a way to participate in different activities in a fun way.” and “It was a great experience. Overall, the assignments were well worked out and I learned a lot”.

Overall, the results indicated that the use of online tools to support blended courses can be a positive experience for all those involved. There was a high percentage of students who recommended the use of a virtual environment as a way to complement the activities carried out in a face-to-face course. From the teacher's point of view, a collaborative environment that aided in formative assessment offered the opportunity to better understand students' behavior and identify alternative methodologies to prevent dropouts.

In addition to this, we also highlighted the contribution of the analysis of LearnWeb, a virtual learning tool not yet used in Brazilian courses. It is also worth noticing that our approach of using EDM techniques to support formative assessment

practices proved to be an effective way to improve the instructor's' decision-making process.

In the future we plan to evaluate the concordance between the perceptions of teacher and students and the data gathered by the logs of the system.

## 7 Acknowledgments

The authors would like to thank the students for their contribution in this research work.

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