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Enhanced online academic success and self-regulation through learning analytics dashboards

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Abstract. In the wake of the COVID-19 health crisis, governments around the world made educational continuity during school and university closure a priority. Many countries adopted online education as an alternative to face-to-face courses. This situation has led to an awareness of the importance of analyzing learning traces and data left by students to measure, evaluate and improve the learning process. This paper presents an interoperable online learning analytics dashboard that allows teachers to easily track the progress of their learners as well as to predict and remedy dropouts. For learners, the dashboard offers the possibility to visualize their learning process, analyze it and develop better self-regulation skills. The results of the study conducted on a blended learning course, showed that the dashboard led learners to spend more time on their online training, to perform the proposed activities much better and to respect the deadlines better, and finally to improve their academic success.

Keywords: Learning experience, Learning analytics, *Self-regulated learning, Learning analytics dashboards, Learner success.*

1 Introduction

In many countries, the COVID-19 pandemic has dramatically accelerated the shift, partially or fully, to online learning in higher education. It is a significant change in the way the student learns and, for the teacher, in the way the educational activities are organized and the student's work is monitored and evaluated. Current learning management systems (LMS) have little or no ability to motivate students and facilitate their work, nor to effectively monitor their work by the teacher. It is therefore necessary to design tools and integrate them into LMS to enable both students and teachers to be effective in online learning, in a general perspective to ensure a good learning experience (LX).

For students, one of the most important factors for success in an online learning environment is the ability to self-regulate their activities. Zimmerman who developed

the theory of self-regulated learning defines self-regulation as “processes whereby students activate and sustain cognitions, affects, and behaviours that are systematically oriented toward the attainment of personal goals” [1].

In theory, learning analytics (LA) and teaching analytics (TA) helps measure and support students' self-regulated learning (SRL) in online learning environments by harnessing the hidden potential of interaction data generated by the use of learning management systems (LMS) [2]. According to Sclater, the goal of learning analytics is to analyze the digital traces left by learners in order to better understand them and optimize learning [3].

However, in a review paper analyzing 54 articles on self-regulated learning and learning analytics [4], Viberg and al. show that there is little evidence of contribution of LA for SRL in these articles. LA performs mainly to measure rather than to support SRL among learners in online environments. Hence, there is a critical need to design tools such as learning analytics dashboard that leverage learner interaction traces to help learner self-regulation.

So, the research challenge is to collect learner interaction traces to analyze them in order to propose an effective visualization of the analysis results to the different users (students and teachers) [5].

In this paper, we propose a learning analytics dashboard which is a visual communication tool, designed as a dashboard for teachers and learners that provides an analysis of learning data to facilitate the monitoring and control of the learning process, with the aim of improving the engagement, enjoyment of learning and success rate of online learners.

This paper begins with a literature review on the influence of self-regulated learning theory and learning analytics on online learners' success. Then, we share the reports of our tool created in the form of learning trace analysis dashboards. The next section is dedicated to the methodology our experiment, and finally the discussions of the results. Finally, we present a conclusion with some perspectives.

2 Related work

2.1 Self-regulated learning theory

Self-regulated learning theory (SRL) defines learning as a dynamic process in which the learner plans, monitors and evaluates his or her learning, applying appropriate strategies to achieve the goals [6]. It is a set of activities that individuals do by themselves in a proactive way [7].

Panadero published an article that presents a review of the six most popular self-regulated learning models [8], the article concludes that, most of these models are composed of three essential phases, namely, (1) the preparation phase, (2) the performance phase, and (3) the reflection phase. As presented in the model of phases and subprocesses of self-regulation by Zimmerman and Campillo [9], the preparation phase includes task analysis, planning, goal detection, and goal achievement; the performance

phase involves the performance of the actual task completed while monitoring and controlling progress; and the final reflection phase, where the learner self-assesses, reacts, and adapts for future performance.

Winne and Hadwin [10] proposed another model of self-regulation composed of four linked phases that are open and recursive and controlled by a feedback loop: (1) task definition (understanding of the task), (2) goal setting and planning (goals and plan to achieve the task), (3) enacting tactics and strategies for learning (actions needed to reach those goals), and (4) adaptations (metacognitive processes for long-term modification of motivations, beliefs and strategies). Each task can be modeled by five facets called COPES model: Conditions, Operations, Products, Evaluations and Standards. The learner's performance depends in part on evaluation (Evaluations facet), i.e. internal and external feedback.

Many studies agree on the relevance of self-regulated learning as a predictor of academic success in online learning systems. Liaw and Huang investigated learner self-regulation to better understand learners' attitudes toward online learning [11]. The results show that the factors perceived satisfaction, perceived usefulness, and interactive learning environments were identified as predictors of perceived self-regulation in the online learning context. In a study on formal and informal learning using social media, the authors showed that the use of social media as pedagogical means, to encourage students to control their autonomies [12].

2.2 Learning analytics dashboards

One of the most common applications of learning analytics is the production of dashboards to provide stakeholders (primarily teachers and learners) with visual interpretations of the overall learning process [13]. Schwendimann defined these tools as a set of single displays that aggregate many indicators about the learning process and/or context into one or more visualizations [14]. In general, these dashboards are steering tools that summarize the company's activities and results by process; thus, allowing to supervise the achievement of any set objective [15].

Jivet [16] proposed a literature review to better understand and describe the theoretical underpinnings behind the use of dashboards in educational settings. The study revealed that the most common foundation for the design of analytic dashboards is SRL. This theory is primarily used in the awareness and triggering of reflection, providing some support for the performance and self-reflection phases of the SRL cycle. A research conducted by Nicholas and colleagues to see how dashboards would be able to predict student outcomes at different points in a course shows that learner outcomes can be predicted with a supervised machine learning algorithm. These predictions were integrated into an instructor dashboard that facilitates decision making for learners classified as needing assistance [17].

In a review paper analyzing 29 learning analytics dashboards (LAD), Matcha and al. [18] find that the information presented in the dashboards is difficult to interpret. They criticize the lack of theoretical grounding of the dashboards (SRL theories is not explicitly considered in the design of LADs), they also note the weaknesses of dashboard evaluations in the experiences described and ultimately their relatively low impact on

learner behavior. The critical analysis of the 29 LADs leads to the proposal of the Model of User-centered Learning Analytics Systems (MULAS) which identifies four dimensions that should be considered by dashboard designers: theory, design, feedback and evaluation.

From this state of the art, we identify two research objectives. First, it is to draw on critical analyses and proposed models in the literature to design a learning analytics dashboard that provides quality and effective feedback to learners and teachers on their learning activity. Second, to conduct an experiment in order to evaluate the contribution of the dashboard to learners' self-regulation and success.

In the following, we present our dashboard called TaBAT for Tableau de Bord d'Analyse des Traces d'apprentissage in French.

3 Design of the learning analytics dashboard TaBAT

LMS platforms provide a variety of integrated reports based on journal data but they are primarily descriptive. They tell participants what happened but not why and they do not predict outcomes or advise students on how to improve their academic performance. These tools are mostly programmed to work with a single platform.

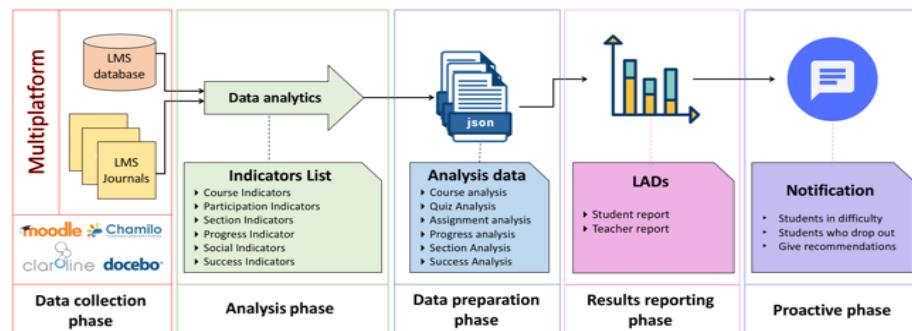


Fig. 1. The phases of the operating process.

Created to work with different online platforms, TaBAT is designed as a dashboard accessible online via the following link <https://safsouf.net/tabat>. It allows to see what happened during the online course (descriptive aspect), to see which students will or will not succeed in the online course (predictive aspect), to know why students were declared as dropouts (diagnostic aspect) and finally to get information on the actions to be taken to improve students' progress and success in the online course (proactive aspect).

As shown in Figure 1, the operating process of TaBAT consists of extracting learner data from data sources (student learning tracks), selecting and calculating assessment indicators, presents reports in various diagrams (based on the learning traces generated from the LMS platform in JSON files to ensure interoperability). Two independent views are presented: the student report and the teacher report.

3.1 Data collection phase

The first phase is to determine the source of the data, choose the LMS, prepare and retrieve the data we use for our reports. The data can be located either in a database in logstore tables (in Moodle for example), log files or both.

3.2 Analysis phase

In this second phase we create analysis algorithms based on the data collected from the previous phase. The goal of these algorithms is to specify and create indicators as well as to analyze student activity traces. The indicators we use are classified into 6 different categories, as follows:

- **Course category:** Gives general information about the course. The three chosen indicators are: the number of students enrolled in the course, the number of sections planned and the number of activities/resources created.
- **Participation category:** This category is more focused on the actions that can be done which consider students active. We distinguish two types of possible actions: consultation actions and contribution actions.
- **Section category:** Here, the two chosen indicators are: the activities/resources consulted by the student within each section (Lessons, Quizzes, Assignments, etc.) and the number of activities/resources contained in each section. These two indicators are used to calculate the student's level of progress in each section of the course.
- **Progression category:** A student's progress represents his or her status within a course. The three chosen indicators for the calculation of progress are: the number of activities the student has already completed, the number of activities not completed in respect of a deadline and the number of activities defined by the teacher at the beginning of the year. The level of progress will also be calculated on the basis of these indicators.
- **Social category:** This category focuses on the social interactions that can take place during the course which considers the students socially active on the LMS.
- **Success Category:** This category is specific to our approach. It is based on our previous research work that models a learner's success in an online course. This category is intended to provide an estimate of a learner's success. In our previous research, we proposed and statistically validated a causal model for evaluating online learner success (e-LSAM) [19]. This model allowed to identify the success factors associated with e-learning and to examine which factors explain a learner's success in an LMS. The result of our study shows that success is explained, with a prediction rate of 80.7%, by 24.1% of self-regulation (represented in our case by the level of progression with success) and by 75.7% of continuity in using the system. The latter is explained by 38.5% of the level of social interaction and 61.5% of the level of course participation.

The indicators presented above give us a numerical value representing the data corresponding to a specific student. We have decided to represent the significance of the numerical data in the form of color indicators.

3.3 Data preparation phase

The third phase plays a main role in the process of our tool, it is the relay between the analysis phase and the results presentation phase. It is also an essential phase to ensure the interoperability of our tool. The goal is to allow, as well as to gather transform and prepare the essential data for our tool in order to generate data in JSON files with a standardized structure. Thus hiding their main source (we are talking here about platforms or data sources) and on the other hand to give the possibility to other developers to extend the use of our tool to other LMS platforms, by using any programming language which allows the generation of these same files (for example: PHP or Python).

3.4 Results reporting phase

In this phase, the reports in form of LADs are presented. These reports communicate directly with JSON files to get the necessary data back. Two aspects are presented independently: the report for the student and for the teacher.

Report for the teacher

The report for the teacher (showed in Figure 2) presents statistical data during the online course. The first page (1) includes the number of students enrolled, the number of sections, activities and resources in the course, the number of students who actively participate in the course, statistics on monthly connections for the current year, as well as statistics on the number of times students consult the activities and resources.

The quiz analysis page (2) provides a table that shows, for each student, the list of quizzes taken or not taken, the number of questions answered, the total number of questions, the final score obtained as a percentage, and the time recorded for taking the test.

The assignment analysis page (3) provides a summary of the assignments that may (on time or late) or may not be returned by students.

The dropout page (4) presents a table that displays the list of students with an estimation of the overall time spent on the course, an indicator representing the level of success (based on the results of our theoretical model called e-LSAM (for e-learner Success Assessment Model) [19], [20]) and finally a prediction status. This status indicates the result of the prediction either: risk of dropping out, minimal risk or success. A color coding allows to visually differentiate if the assignment is submitted or not, if the quizzes are done or not and the risk of dropping out or not.

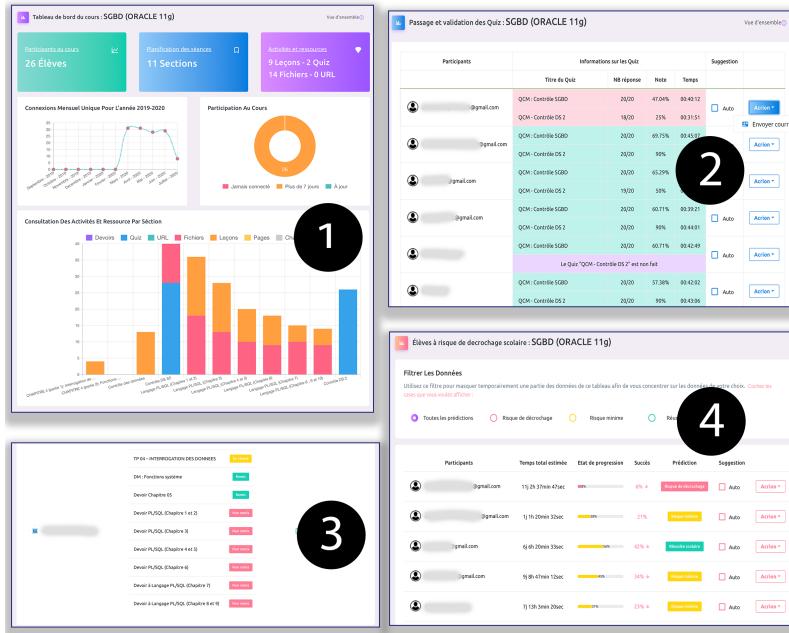


Fig. 2. General view of report of the teacher dashboards.

Report for the student

The report for the student gives an overall view of each student's progress in the course. The three available interfaces are shown in Figure 3.

The first interface (1) gives a positioning of the student's progression level for each section of the course with two other levels: the level of progression of the best student and the level of the average student in the class. It also displays a ranking table of all learners in the class. This interface aims to motivate and support students' metacognition and self-regulation processes.

For the second interface (2), the student can see the details of his/her progress in the course. A chart presented in the form of a vertical progress bar summarizes the student's progress for each section of the course. This interface displays the details of the student's progress in each section.

The last interface (3) is the notification interface. Here the student can view the list of notifications (marked as unread) sent automatically by the system. Notifications are displayed by type, with a message indicating the actions to be taken. A script is scheduled to send notifications automatically twice a day; at 08:00 in the morning and again at 08:00 in the evening. If the same notification has already been sent and has not been read yet, the sending is not done.

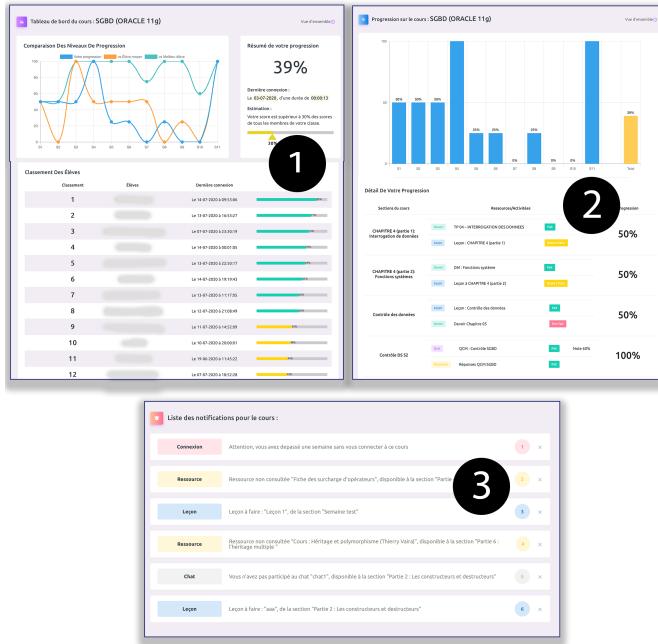


Fig. 3. General view of report of the student dashboards.

3.5 Proactive phase

This last phase allows the teacher to contact the students manually or to schedule automatic notifications. The goal is to have alerts on the student's side about a variety of available actions. The last three pages of the report for the teacher (2,3 and 4), gives him the opportunity to select the learner(s) who will receive automatically suggestions (or notifications) regarding their achievements, assignments to submit or quizzes to do, resources to consult or even lessons to view. Each page also includes a contact button to send the student an email.

4 Methodology and date analysis

4.1 Context of the study and participants

This study aims to see the impact of the TaBAT dashboard, on the self-regulation and prediction of success of students in a higher institute in Morocco (ISGA of Marrakech).

The target population is composed of 46 students who have participated in a course organized in a mixed modality. The class is divided into two groups of 23 students each (15 female and 21 male), aged between 18 and 35 years (39 between 18 and 25 years and 7 between 26 and 35 years). In terms of time of use of the Internet and computer

devices per day, 5 students reported their time of use to be between two and five hours, 31 between five and ten hours, and another 10 more than ten hours per day.

4.2 Study Methodology

The course was available in a blended learning format, which combines face-to-face and online training. Students in both groups, all took a face-to-face course entitled "Object Oriented Programming", with some chapters online on the Moodle 3.8 platform, over an eight-week period, finalized by a supervised face-to-face exam.

To evaluate the impact of using the tool on self-regulation and prediction of student success online, one of the two groups was given the experiment to use the TaBAT tool (exposed group), while the second group did not have access to the dashboard (control group).

4.3 Study results

The part of the online course followed by all students consists of 7 sections (parts), with 7 lessons, 3 files to download, 7 URL links to visit, and 2 assignments due on dates planned at the beginning of the course. The analysis of the individual student traces in each group was done using the TaBAT dashboards via the teacher report. Table 1 describes the result of the experiment conducted on the two groups.

Table 1. Usage statistics of the TaBAT tool.

	Exposed group	Control group
Number of active users	23/23	21/23
Cumulative time to complete the course	129 h 15 min	78 h 37 min
Percentage progress score	Max	100%
	Min	52%
	Average	73.21%
Percentage of assignments	Returned on time	81.22%
	Returned late	11.62%
	Not returned	7.16%
Prediction of success (online success)	23/23	16/23
Effective success (validation of the face-to-face exam)	20/23	18/23

4.4 Discussion

We note at first that the 23 students in the exposure group all logged into the online course, while for the control group, 2 students did not take the online part of the course. This is because for the control group, the only way to communicate with the teacher

was face-to-face. Whereas for the exposed group, the teacher had the possibility through the TaBAT dashboard to contact each student via e-mail, which allowed for individual monitoring.

The second observation concerns the total time spent doing the online course activities. This time is represented in Table 1, cumulated for each group. Students in the exposure group spent significantly more time (65% more) than those in the control group following and completing the online course activities and resources. This increase thus reflects independent functioning and resistance to distractions, thus making work at home a particular form of self-regulated learning.

The third remark concerns the performance of each group, this performance is represented in Table 1 by three score values, the maximum, minimum and average score of progression in the online course. The progress of each student represents the number of activities or resources consulted or accomplished over the number of activities or resources defined by the teacher at the beginning of the course. We notice a significant improvement in the performance of the exposed group mainly by an increase in the minimum value (3.25 times more) and the average progress (28% more) of the participants. This progression is mainly explained by the proactive actions made manually by the teacher or sent automatically by the TaBAT tool (proactive phase), in order to remind the students (with the help of notifications) if they have not yet accessed certain resources (file to download or url to visit) or unaccomplished activities (lesson, homework, quiz to do, etc.). Not to mention the important role of the student report which allows students to self-assess and follow metacognitive strategies to improve their online performance.

The fourth remark concerns the analysis of the return of homework. Indeed, the exposed group had a rate of 92.84% of assignments (planned at the beginning of the course) returned on time (assignments returned on time with those returned late), while for the control group, the same rate was 73.66%. This significant improvement is particularly due to the notifications received if there is an assignment due or not handed in on time (late). The notification includes the date and the number of days to hand in the assignment.

The final point concerns student success. In this study, the level of success calculated by the TaBAT tool based on our online learner success assessment model (e-LSAM) is compared to that obtained after the final exam. Table 1 shows that the TaBAT tool was able to demonstrate a high ability to predict the success of students for both groups in our experiment.

5 Conclusion

The development, implementation and experimentation of the learning analytics dashboard TaBAT represents the completion of our modeling work, which was design to identify factors that reduce the dropout rate of learners, and at the same time improve their success in online courses.

We proposed in this paper a study to test the effectiveness of the learning analytics dashboard TaBAT in the analysis of learning traces in an online course planned by an

engineering school in Morocco. The results of this study confirmed that the use of TaBAT increased the learners' performance, improved their autonomy, and finally improved their academic success.

In our future work we would like to extend the use of TaBAT to other online courses (of different natures and specialties), in order to generalize our experience and to see the impact of the tool on the performance and the real success of learners.

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