



HAL
open science

Experimental Design of Learning Analysis Dashboards for Teachers and Learners

Yassine Safsouf, Khalifa Mansouri, Franck Poirier

► **To cite this version:**

Yassine Safsouf, Khalifa Mansouri, Franck Poirier. Experimental Design of Learning Analysis Dashboards for Teachers and Learners. L@S '21: Eighth (2021) ACM Conference on Learning @ Scale, Jun 2021, Virtuel, Germany. pp.347-350, 10.1145/3430895.3460990 . hal-04084061

HAL Id: hal-04084061

<https://hal.science/hal-04084061v1>

Submitted on 27 Apr 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Experimental design of learning analysis dashboards for teachers and learners

Yassine SAFSOUF

Laboratory LIMIE, ISGA Group,
Marrakesh, Morocco
yassine.safsouf@isga.ma

Khalifa MANSOURI

Laboratory SSDIA, University
Hassan II Casablanca, Morocco
khmansouri@hotmail.com

Franck POIRIER

Lab-STICC, University Bretagne
Sud, Vannes, France
franck.poirier@univ-ubs.fr

ABSTRACT

Since learning in higher education is increasingly taking place online, the multiplication of web-based educational content, learning management systems (LMSs) and collaborative communication platforms have generated a large volume of data on learners and their learning activities. In recent years, interest has been growing in analyzing this data to support real-time decision making and improve the learning experience. This paper presents the results of a study conducted in higher education in Morocco, which evaluates a learning analysis dashboards (LADs) for both teachers and learners. The study shows that the dashboard, called TABAT, allowed a synthetic visualization of learning progress in courses and led to improved student engagement and success rates.

Author Keywords

Information visualization; Learning analytics; Learning analytical dashboard; Self-regulated learning; Higher education.

INTRODUCTION

A dashboard is not only a simple display of indicators, but most importantly is a decision-making tool. Yigitbasioglu presents dashboards as a "solution that should improve decision making by amplifying perception and capitalizing on human perceptual capacities" [8]. The two management experts Robert S. Kaplan and David Norton see the dashboard as a management tool. They concluded by observing companies in the United States. In 1996, they created a strategy management system in the form of dashboards, named Balanced Scorecard [4], whose purpose is to build and steer the implementation of strategy.

Learning Analytics (LA) aims to exploit the hidden potential of interaction data generated by the use of online learning environments. This is a relatively new field created in 2011 and defined as the detection, collection, analysis and exploitation of digital traces left by learners in their daily activities. In order to understand and optimize learning and

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
L@S'21, June 22–25, 2021, Virtual Event, Germany.
© 2021 Association for Computing Machinery.
ACM ISBN 978-1-4503-8215-1/21/06...\$15.00.
DOI: <https://doi.org/10.1145/3430895.3460990>.

the different environments in which it occurs [7]. However, the diversity of existing learning management systems (LMS) complicates the task of analyzing all these data, which is further amplified by the need to combine data from a variety of sources. The main challenge would be to have a system to analyze learning data in such a way that the precise meaning of the data is easily accessible and could be translated into an understandable format regardless of the LMS or technological environment used.

This paper proposes a presentation of a multi-platform visual communication tool designed in the form of dashboards for teachers and learners. Our goal is to conduct a learning analysis to facilitate the monitoring and control of the learning process in order to improve the success rate of learners. In the rest of the paper, we will present related work in the field of learning analysis in section 2, we will also present our tool created in the form of learning trace analysis dashboards in section 3. Section 4 will be dedicated to the methodology, context and data analysis of the study. A discussion of the results obtained will be detailed in section 5, followed by a conclusion.

RELATED WORK

LA is an emerging trend in Morocco, particularly in higher education. The development of big data technologies and the widespread use of digital tools allow us to build up important data collections on student behavior. We can now measure, collect, analyze and process this data in order to better understand learners and improve their learning levels [7]. Reports of LA approach are usually communicated to teachers and students through dashboards or personal emails. The value of these computerized systems is to promote academic success as well as to improve students' self-regulated learning (SRL) [1], but also to facilitate and improve the monitoring of students by their teachers.

Learning Analytical Dashboards (LADs) can give students a single display that combines multiple visualizations of different indicators on their learning processes [6]. LADs primarily aim to improve students' self-awareness which leads to improved academic performance as well as enhanced SRL. Several tools have been created in this sense, for example the NoteMyProgress plugin for Moodle, which aims to support students' self-regulation capacity in online and hybrid learning environments [3].

Commenté [P1]: skill (à la place de capacity)

LADs can also provide teachers with important information about their students, including time spent, resource use and social interactions. The goal is to help teachers to understand learning processes and create predictive models to improve student outcomes. In research conducted by Nicholas et al. [2], to see how LADs can predict student outcomes at different points in a course. The results show that student outcomes can be predicted with a supervised machine learning algorithm. Most of the commercial solutions are dedicated to a single LMS. Unfortunately, the diversity of existing LMSs complicates the analysis of this data. A situation that is further amplified by the need to combine data from various sources. The contribution of our work would be to have a system that can analyze learning data in a way that provides accurate and meaningful dashboards for both teachers and students, regardless of the platform or technological environment used.

TABAT TOOL DESCRIPTION

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. In this paper, we propose a presentation of an interpretable tool (functional with different LMSs) that we have created as LADs. With our dashboard, we can consult what happened during the online course follow-up (descriptive aspect), see who are the students who will or will not succeed in the course (predictive aspect), find out why students have been declared as dropouts (diagnostic aspect) and finally get information on what actions to take to improve the progress of students in the course (proactive aspect).

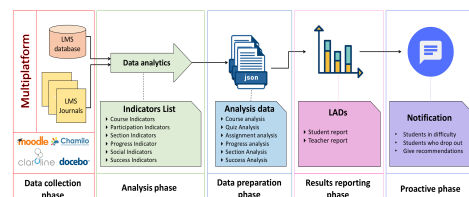


Figure 1: The phases of the operating process of our tool.

As shown in Figure 1, the operating process of our proposed LAD consists of extracting learner data from data sources (Student Learning Tracks), selecting and calculating assessment indicators, generating JSON files that hide the source of the collected data and finally visualizing the results of the reports in the form of a LADs.

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.

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:** The last category is intended to provide an estimate of a learner's success level in an online course. According to our previous research, where we proposed and statistically validated in online learner success assessment model (e-LSAM) [5]. This model allowed us 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.

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).

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.

The report for the student presents a clean and efficient synthetic vision of a student's progress in an online course. The three available interfaces are shown in Figure 2. 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 or her progress in the course. The progress detail is displayed in a table below the graph. 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.

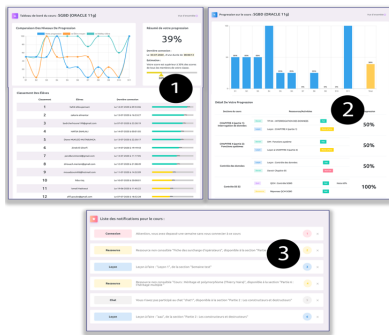


Figure 2. Dashboards summarizing the report for the student.

A script is programmed to send notifications automatically twice a day; at 08.00 in the morning and again at 20.00 in the evening. If the same notification has already been sent and hasn't been read yet, the sending is not done.

The report for the teacher (showed in Figure 3) presents statistical data (from the indicators in the course category) during the course as well as the summary graphs on the consultation of students in the class for each section of the online course as shown in the first interface (1). The quiz

analysis page (2) provides a table that shows, the list of the quizzes taken and validate or not by students. The assignment analysis page (3) provides a summary of the assignments that may or may not be returned by students.

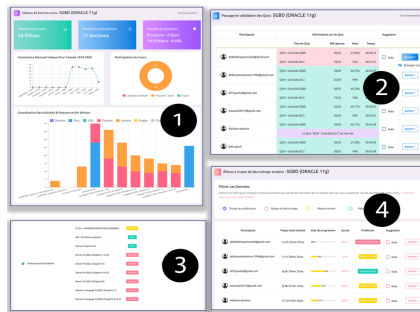


Figure 3. Dashboards summarizing the report for the teacher.

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 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 differentiate visually if the assignment is submitted or not, if the quizzes are done or not and the risk of dropping out or not.

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.

STUDY CONTEXT AND RESULTS

The main objective of this study is to test the TaBAT tool and assess its impact on self-regulation and prediction of success for 26 students enrolled in the second year of the engineering cycle at the Higher Institute of Engineering and Business (ISGA of Marrakech) in Morocco. Based on the decisions made to minimize the hygiene and sanitary risks caused by COVID-19, the institute has reduced the number of students to groups of 10 to 14 students, with respect for physical distance between students in different groups. The students all completed the classroom course entitled "Object-Oriented Database", with some online sections on the Moodle 3.8 platform, over an eight-week period, completed by a supervised exam.

The target class is divided into two groups of 13 students (8 female and 18 male), aged between 18 and 35 years old (24

between 18 and 25 and 2 between 26 and 35). In terms of time spent using the Internet and computer per day, 6 students reported using the Internet between two and five hours, 18 between five and ten hours, and 2 more than ten hours per day. One of the two groups had access to the experiment to use the TaBAT tool (exposed group), while the second group did not (control group).

| | Exposed group | Control group |
|---------------------------------------------------------|---------------|---------------|
| Number of active users | 13 | 11 |
| Cumulative time to complete the course | 45 h 57 min | 15 h 57 min |
| Average percentage progress score | 85,54 % | 37,61 % |
| % of assignments returned on time | 44,23 % | 11,54 % |
| % of assignments returned late | 26,92 % | 15,38 % |
| % of assignments not returned | 28,85 % | 73,08 % |
| Prediction of success (online success) | 13/13 | 8/13 |
| Effective success (validation of the face-to-face exam) | 13/13 | 9/13 |

Table 1. Study results obtained from the TaBAT tool.

The analysis of student tracks in each group was done using the dashboards of the TaBAT dashboard via the report of the teacher. Table 1 describes the results of the experience.

RESULTS DISCUSSION

We note at first that all students in the exposed group logged on to the online course, while for the control group, 2 students did not take the online part of the course. The second remark concerns the total time spent doing the activities of the online course. Students in the exposed group spent almost triple the amount of time that students in the control group took to complete the online course. This increase therefore reflects self-directed 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. We notice a significant increase in the average progression score of the exposed group, explained by the proactive actions done manually by the teacher or sent automatically by the TaBAT tool (proactive phase), in order to remind students if there are still resources not consulted (file to download or URL to visit) or activities not completed (lessons, homework to return, quizzes to do, etc.).

The fourth remark concerns the analysis of the assignments. In fact, the exposed group had a 71.15% return rate for assignments, while for the control group, the same rate was 26.92%. This result is due in particular to the notifications received. The last remark concerns the success of the students. In this study, the level of success calculated by the TaBAT tool is compared to that obtained after the final exam. The TaBAT was able to predict 100% success for students in the exposed group and 80% success for students in the control group. This result shows that students' performance and success is partly due to their ability to provide effective work at home, better preparing them for the classroom tests.

CONCLUSION

This paper presents a new learning analysis dashboard, based on a theoretically validated model. Our dashboard allows to visualize the learners' progression as well as the prediction of student dropout rates. After a first study, we can conclude that the tool has provided useful and clear information to motivate and regulate the students' effort, as well as helping the teacher to monitor the students and detect dropouts. We will conclude by mentioning that this first study has two limitations, first of all, this study is limited to one class, the integration of several classes into the study would require more resources. Finally, due to this sample size limitation, more statistical analyses were not conducted. These initial results are very encouraging and will need to be confirmed in a more extensive study.

REFERENCES

- [1] Eva Durall and Begoña Gros. 2014. Learning analytics as a metacognitive tool. *CSEdu-Proc. 6th Int. Conf. Comput. Support. Educ.* 1, (2014). DOI:<https://doi.org/10.5220/0004933203800384>
- [2] Diana Nicholas, Shuchi Grover, Michael Eagle, Marie Bienkowski, John Stamper, and Satabdi Basu. 2017. An instructor dashboard for real-time analytics in interactive programming assignments. *ACM Int. Conf. Proceeding Ser.* (2017), 272–279. DOI:<https://doi.org/10.1145/3027385.3027441>
- [3] Ronald Pérez-álvarez, Jorge Maldonado-Mahauad, and Mar Pérez-Sanagustín. 2018. Design of a tool to support self-regulated learning strategies in MOOCs. *J. Univers. Comput. Sci.* 24, 8 (2018). DOI:<https://doi.org/10.3217/jucs-024-08-1090>
- [4] David P. Norton Robert S. Kaplan. 1996. *The Balanced Scorecard: Translating Strategy into Action.*
- [5] Yassine Safsouf, Khalifa Mansouri, and Franck Poirier. 2020. An analysis to understand the online learners' success in public higher education in morocco. *J. Inf. Technol. Educ. Res.* 19,(2020). DOI:<https://doi.org/https://doi.org/10.28945/4518>
- [6] Beat A. Schwendimann, María Jesús Rodríguez-Triana, Andrii Vozniuk, Luis P. Prieto, Mina Shirvani Boroujeni, Adrian Holzer, Denis Gillet, and Pierre Dillenbourg. 2016. Understanding learning at a glance: An overview of learning dashboard studies. *ACM Int. Conf. Proceeding Ser.* DOI:<https://doi.org/10.1145/2883851.2883930>
- [7] George Siemens and Dragan Gasevic. 2012. Learning analytics special issue. *J. Educ. Technol. Soc.* 15, 3 (2012), 1–2. Retrieved from http://www.ifets.info/journals/15_3/ets_15_3.pdf
- [8] Ogan M. Yigitbasioglu and Oana Velcu. 2012. A review of dashboards in performance management: Implications for design and research. *Int. J. Account. Inf. Syst.* 13, 1 (2012), 41–59.