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TABAT: DESIGN AND EXPERIMENTATION OF A LEARNING ANALYSIS DASHBOARD FOR TEACHERS AND LEARNERS

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ABSTRACT

Aim/Purpose	Since the beginning of the COVID-19 pandemic, many countries have adopted online education as an alternative to face-to-face courses. This has increased awareness of the importance of analyzing learning data left by students to improve and evaluate the learning process. This article presents a new tool, named TaBAT, created to work with different LMSs in the form of dashboards accessible online and allowing teachers to monitor the progress of their learners and at the same time allow learners to visualize their learning process.
Background	TaBAT is designed based on the results of our previous research on factors that can influence the success of online learners, where we proposed and statistically validated a model for assessing the success of online learners called e-LSAM (e-Learner Success Assessment Model).
Methodology	Two studies are presented in this article. The first one is conducted on a group of students from two classes (each composed of two groups) of a higher institute in Morocco, who participated in courses organized in blended learning on the Moodle platform. For each class, one of the two groups had access to the experiment to use the TaBAT tool (exposed group) to analyze the learning traces, while the second group did not have access to the dashboard (control

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	group). The second study aimed to understand the impact of the usage of the TaBAT tool on the two exposed groups.
Contribution	The purpose of this article is to present a new analysis tool as well as to test this tool and to evaluate its impact on self-regulation and the prediction of academic success and, finally, to see how these students evaluate this tool.
Findings	The results of the TaBAT usage demonstrate the effectiveness of the success algorithm, based on our theoretical model e-LSAM. The results also prove that this tool was able to increase the performance of the students of both groups exposed. The general evaluations of the participants also confirmed these results.
Impact on Society	The article proposes a tool for institutions to facilitate the monitoring and control of students' learning process. The tool provides visual information for teachers to study and react to in the educational context and gives students visualizations to promote their self-reflection and increase their performance and academic success.
Future Research	Generalize the use of the TaBAT tool, incorporating both private and public institutions, in order to confirm the results obtained in this article and at the same time improve the self-regulation and academic success of learners.
Keywords	information visualization, learning analytics, learning analytical dashboard, self-regulated learning, higher education, e-learning, learners' success

INTRODUCTION

Learning analytics (LA) is a discipline that aims at exploiting the hidden potential of interaction data generated by the use of online learning environments (Ferguson, 2012). Its main challenges are to collect learner interaction traces, to analyze them and to propose a display of analysis results to different users (Labarthe & Luengo, 2018). It is therefore necessary to offer them displays adapted to their needs, mainly in the form of dashboards (Nicholas et al., 2017).

A dashboard is not only a simple display of indicators, but most importantly is a decision-making tool. Yigitbasioglu and Velcu present dashboards as a “solution that should improve decision making by amplifying perception and capitalizing on human perceptual capacities” (Yigitbasioglu & Velcu, 2012). In the field of education, a learning dashboard is defined as a single display that groups different indicators about the learner, the learning process(es) and/or the learning context(s) using one or more visualizations (Schwendimann et al., 2017). In higher education, the use of learning dashboards has indeed become a necessity. Higher education institutions have come to confront many challenges, especially in terms of student success and cost reduction. By using data analysis and representation tools to generate useful reports, some organizations are turning these challenges into assets. For example, Brockenhurst College (New Forest, England) used dashboards generated by IBM Cognos Business Intelligence (an integrated web-based intelligence suite by IBM) to provide management with better analysis of student performance. Brockenhurst College found that tracking student progress improved student retention by 15% due to student satisfaction and awareness of the changes needed to track their success. Another research conducted in Florida State University discovered that students who earned a “F” or “D” in a class used a tracking system to monitor their academic progress 40% less than those who earned a “C” or more (Powers, 2011).

Learning analytics is a new field that has chosen to build these analysis processes in connection with users (Dabbebi, 2020). According to Sclater (2017), the goal is to analyze the digital traces left by learners in order to better understand them and optimize learning. In fact, learning analytics focuses on the detection, collection, analysis and exploitation of digital traces left by learners in their daily activities, in order to understand and optimize learning and the different environments in which it

occurs (Siemens & Gasevic, 2012). However, the diversity of existing learning management systems (LMS) complicates the task of analyzing this 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.

Our study is part of this context. In this paper, we propose an interpretable visual communication tool, designed as a dashboard for teachers and learners and providing an analysis of learning data in order to facilitate the monitoring and control of the learning process, with the aim of improving the engagement and success rate of online learners.

In the rest of the paper, we present a literature review in the field of learning analysis and describe the research context. Then we share our tool created in the form of learning trace analysis dashboards. The next section is dedicated to the methodology and data analysis of our tool usage study with discussions of these results. The results of a second qualitative study are then detailed and discussed, followed by a conclusion.

LITERATURE REVIEW

LA is an emerging trend in Morocco, particularly in higher education. The development of big data technologies and the widespread use of digital tools (thus the traces left by students) 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 (Siemens & Gasevic, 2012). Reports of LA approach are usually communicated to teachers and students through dashboards or personal emails (Biggs, 2012). The value of these computerized systems is to promote academic success as well as to improve students' self-regulated learning (SRL) (Durall & Gros, 2014). Learning analytical dashboards (LADs) can give students a single display that combines multiple visualizations of different indicators on their learning processes (Schwendimann et al., 2016). LADs primarily aim to improve students' self-awareness, which leads to improved academic performance as well as enhanced SRL, as defined by Zimmerman and Moylan (2009) in their SRL cycle (performance and self-reflection phase). Jivet et al. (2018), in a literature review on the use of educational concepts in LADs for learners, state that the majority of LADs aim to support the metacognitive level of learners and very few aim to support the cognitive or emotional level. However, care must be taken from the outset when integrating these dashboards. Toohey et al. (2019), at Murdoch University in Australia, conducted a study to examine learners' perceptions of LADs and to explore how learners perceive that their motivation would be influenced by the use of these dashboards. The results show that more than 90% of the learners in this study preferred that the information displayed about their rankings on the LADs remain private, primarily for reasons associated with added stress or demotivation. The effects of good and bad ranking on learners were also observed. Indeed, learners who viewed the dashboard showing them as well graded were more likely to be more motivated to study. Based on the results reported in this study, it would appear that the implementation of LADs for learners should be done with caution.

Ruipérez-Valiente et al. (2015), from the University Carlos III of Madrid, have identified two main approaches to the use of LA to evolve education, both in the classroom and at a distance. The first one is the direct communication of data through dashboards, aiming at providing students visualizations to foster their self-reflection, and giving teachers visual information so that they can study and react to them considering the educational context. Thus, stakeholders make final decisions using the visual information provided. The second approach is the construction of systems that rely on artificial intelligence algorithms for automatic data processing (Atkinson, 2015), such as intelligent tutoring systems, reminder systems or adaptive systems, which take into account different variables related to the learning process in order to achieve their actions. These two approaches, corresponding to two paths of the LA, give rise to its own pools of researchers. In fact, according to a study made in 2019 on the hybrid analysis between the LA communities (Labarthe et al., 2019), three communities have

been formed on an international scale. The oldest one is the AIED (Artificial Intelligence in Education) created in 1993, which has had an annual international conference of the same name since 1999, as well as a journal called IJAIED (*International Journal of Artificial Intelligence for Education*). At the beginning of 2008, two other communities gradually appeared, the IEDMS (International Educational Data Mining Society) and the SoLAR (Society for Learning Analytics Research). The first one designates an annual international conference named EDM (Educational Data Mining) with a journal dedicated to this field, the JEDM (*Journal of Educational Data Mining*). The second is more recent, created in 2011, and associated with the international conference LAK (Learning Analytics for Knowledge) and the journal JLA (*Journal of Learning Analytics*). Although all three communities have tackled similar issues and share similar goals, they have developed separately with different approaches (Labarthe & Luengo, 2018). Researchers in AIED, as in EDM, use more artificial intelligence algorithms (data mining, machine learning or deep learning) to analyze data from LMS, in order to establish the best possible predictions (Liu & Tan, 2020; Mao et al., 2018). However, in SoLAR, modeling, relationship exploration and data visualization (in the form of LADs) are transferred to the main actors of the LMS (Fincham et al., 2019; Millicamp et al., 2018). In the first approach, the aim is to design automatic monitoring, adaptation and personalization systems that do not require the intervention of a teacher or a student. However, the researchers at SoLAR, focus on the possibility of giving autonomy to the actors of learning, thus covering a wider range of possibilities, without forgetting the fact that algorithms can sometimes make more mistakes in their decisions than human persons (Siemens & Baker, 2012).

LADs can 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. The results of research conducted by Nicholas et al. (2017), to see how LADs can predict student outcomes at different points in a course, reveal that student outcomes can be predicted with a supervised machine learning algorithm. These predictions have been integrated into an instructor dashboard that facilitates decision making for those students ranked as the neediest for assistance. A thesis by Ines Dabbebi (2020), in the context of the ANR HUBBLE project, aimed at the creation of a national observatory and a repository of high-level analysis processes. The goal of this thesis was to design a process for generating learning dashboards, allowing to automatically introduce and take into account the users' needs

Several commercial solutions also offer LADs that give teachers an overview of the student's education process. The Inspire plugin (Monllaó & Dalton, n.d.) of the Moodle LMS implements an analysis of learning and providing predictions on learner success, diagnostic and advice to both learners and teachers. Unfortunately, this plugin is only functional for Moodle 3.4. Analytics (Moodle, 2019). This plugin aims to predict or detect unknown aspects of the learning process, based on historical data and current behavior. This plugin supports two types of models: (i) models based on Machine Learning; and (ii) "static" models to detect situations of concern using simple rules. As for the Inspire plugin, Analytics is only functional with version 3.4 or higher. One of the innovative projects in French higher education funded by the Apereo consortium is the Apereo's Learning Analytics Initiative (LAI) project (Seclier, 2017). The objective of this project is to provide a free open-source platform for collecting, storing and analyzing learning related data mainly from the Moodle LMS. Apereo's platform also consists of a web-based dashboard application based on the data in the database. This application is also open-source and can be downloaded cost free (Apereo Foundation, 2021). 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.

RESEARCH CONTEXT

There are four main categories of LA: (i) descriptive aspect to answer the question of what happened; (ii) predictive aspect to answer the question of what will happen next; (iii) diagnostic aspect to understand why it happened; and (iv) the proactive aspect to know what to do to improve.

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 and named TaBAT. With our tool, 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).

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, generating JSON (JavaScript Object Notation) files that hide the source of the collected data and, finally, visualizing the results of the reports in the form of a LADs.

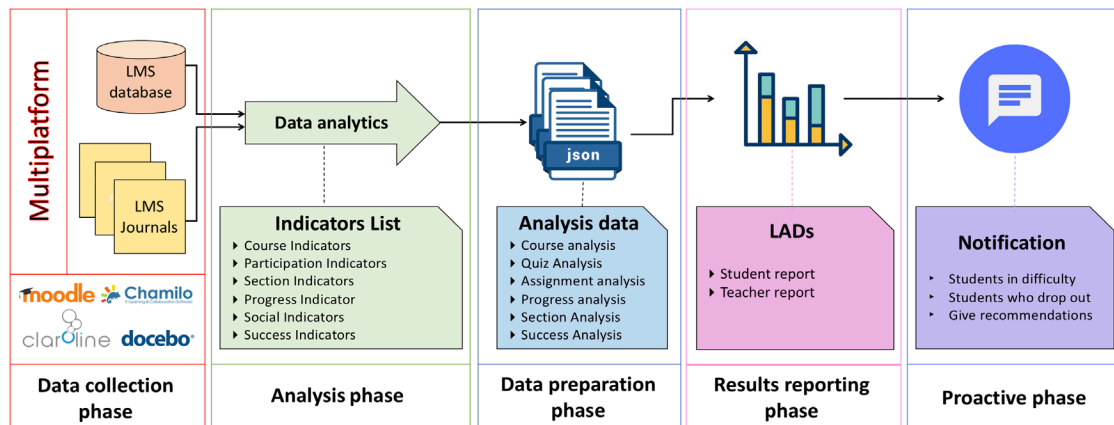


Figure 1. The phases of the operating process of our tool

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 (MySQL, MariaDB or PostgreSQL) in logstore tables (in Moodle, for example), log files or both. In this phase the user can choose the platform and create a configuration file (containing the access link to the platform, the database connection string, the table prefix as well as the login and password to access the database) in order to access the learning traces.

ANALYSIS PHASE

In this second phase, we create analysis algorithms based on the data prepared and 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 six different categories, as follows:

1. **Course category:** This 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.
2. **Participation category:** This category is more focused on the actions that can be done on the course which consider students active. We distinguish two types of possible actions: consultation actions and contribution actions. Four indicators are chosen: the date of the last action made in the course, the total duration of the actions done in the last session, the total duration of the actions done since the beginning of the course, and the number of actions done by a student for each type of action. The participation level is also calculated for each student, using the following formula:

$$Participation = \frac{\text{Cumulative duration of actions performed since the beginning of the course}}{\text{Max (Cumulative duration of actions performed)}}$$

3. **Section category:** Here, the two chosen indicators are: the activities/resources consulted by the student within each section (Lessons, Quizzes, Assignments, URLs, Chat, Files, 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:

$$Section\ progress = \frac{\sum_i^n (\text{activities \& resources consulted})_i}{\text{Number of section activities}}$$

4. **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. These three indicators directly represent the student's progress within the course and therefore his or her personal progress. The level of progress will also be calculated on the basis of these indicators, using the following formula:

$$Course\ progress = \frac{\sum_i^n (\text{indicator activity accomplished})_i}{\text{Total number of activities}}$$

5. **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. Four indicators are chosen: the **number** of messages posted by users in the two activities Chat and Wiki, the total number of messages from the same activities, the number of messages sent or received in a course's chat or wiki, and the total number of internal messages sent or received in the course. The social level is then calculated using these indicators. The formula used to calculate this level is:

$$Social = \frac{\sum_i^n (\text{chat and wiki message indicator})_i + \sum_i^n (\text{LMS message indicator})_i}{\text{Number of course chat messages} + \text{Number of LMS course messages}}$$

6. **Success Category:** The last category is intended to provide an estimate of a learner's success level in an online course. The first of two chosen indicators is the level of progression with **success**, i.e. with passing (above average score), and the tests (quizzes), assignments and lessons. This indicator will be calculated as follows:

$$Progress\ with\ success = \frac{\sum_i^n (\text{indicator successfully completed activity})_i}{\text{Total number of activities}}$$

The second indicator is more global, as it gives a general idea of the level of success of a learner in an online course. According to our previous research, we proposed and statistically validated our online learner success assessment model (e-LSAM) (Safsouf et al., 2019, 2020). 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. In order to give an accurate calculation value, we preferred to round the values for the level of social interaction to 40% and the level of course participation to 60%. The equation for determining the continuity of use of the system will be as follows:

$$\text{Continuity} = (0.4 \times \text{Social level}) + (0.6 \times \text{Participation level})$$

As for the calculation of the continuity of use of the system, we have rounded the level of self-regulation to 30% and the level of continuity of use to 70%. The success level is represented by the following equation:

$$\text{Success} = (0.3 \times \text{Progress with success}) + (0.7 \times \text{Continuity})$$

The indicators presented above give us a numerical value representing the data corresponding to a specific student. In the following, we represent the significance of the numerical data in the form of color indicators. Three colors are chosen: (i) green color means that the student participates actively on the platform; (ii) yellow means that the student could be more involved on the platform despite the fact that he or she is already there; and (iii) red means that the student does not participate enough in the online course and must absolutely change the way of working. Of course, each color indicator must be analyzed according to the criteria it represents.

DATA PREPARATION PHASE

The third phase plays a main role in the process of TaBAT; 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, hide their main source (platforms or data sources) and, on the other hand, give the possibility for other developers to extend the use of our tool to other LMS platforms by using any programming language that allows the generation of these same files (e.g., 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 the report 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 report for the teacher presents statistical data (from the indicators in the course category) during the course as well as the summary graphs (from the indicators in the participation and section categories) on the consultation and contribution of students in the class for each section of the online course.

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. We have classified these notifications into six categories:

1. **Connection:** The student receives a connection type notification if he/she exceeds 7 days without being connected to the LMS platform.
2. **Resource:** The student receives a resource type notification if he/she has not consulted a resource (file to download or ULR to visit).
3. **Social:** The student receives a social notification if he/she has not contributed to a social activity (chat or wiki).
4. **Lesson:** The student receives a lesson type notification if he/she has not consulted or completed a lesson planned in a section of the course.

5. **Test:** The student receives a test (quiz) notification if there is a test available. The notification includes the date and time scheduled by the teacher.
6. **Assignment:** The student receives an assignment notification if there is an assignment that has not yet been submitted or if the deadline for submission has been extended. The notification includes the date and the last deadline (number of days) for submitting the assignment.

Each type of notification is color-coded for easy viewing and quick detection of important notifications.

DASHBOARD TOOL INTERFACES

Based on the data generated in the JSON files (data preparation phase), we chose to design our interfaces respecting the essential needs of the teachers and the students. The interfaces include graphs, tables, as well as color codes (red = danger, yellow = warning, and green = satisfactory). In this section, we present the interfaces of both reports previously presented in the results reporting phase.

REPORT FOR THE TEACHER

As presented in the results reporting phase, a report in the form of LADs is offered for teachers. Figure 2 shows a full-screen view of the dashboards summarizing the report for the teacher.

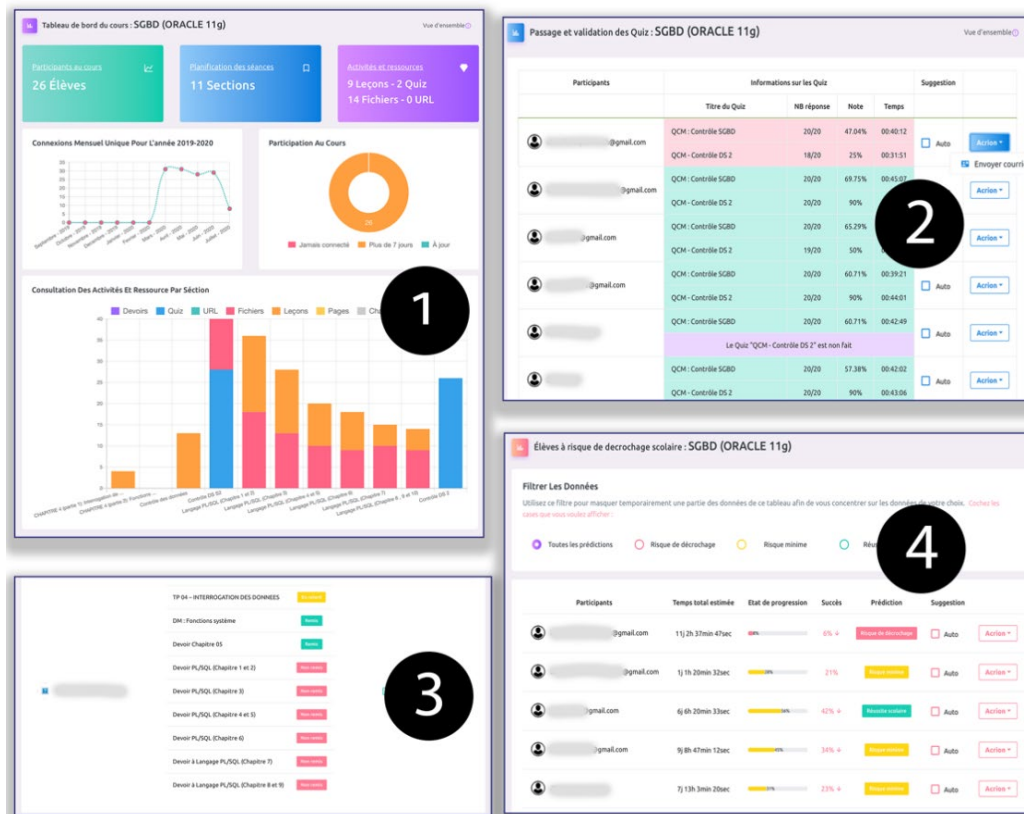


Figure 2. Full screen view of the dashboards summarizing the report for the teacher

The first page (1) gives a summary of the course. This page 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 or may not be returned by students. The assignment is presented by title and status. The dropout page (4) presents a table that displays the list of students with an estimation of the overall time spent on the course (calculated on the basis of the sum of the duration of the actions counted for each student), a progress status with validation (i.e. counting only the number of valid quizzes with the level of social participation), an indicator representing the level of success (the calculation is based on the results of our theoretical model [Safsouf et al., 2019, 2020]), an arrow pointing up or down indicating either the increase or decrease of the level of success compared to the last recorded value (this arrow is not displayed if the level does not change) and, finally, a prediction status (this status indicates the result of the prediction either: risk of dropping out, minimal risk or success). The last three pages (2, 3, 4), allow the teacher to choose the student(s) who will receive automatic suggestions regarding their achievements, the submitted assignments or the quizzes that are not done. Each of these pages also has a button to contact the student by email. 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. The dropout page also offers a methodology for filtering the result. The check boxes allow the user to specify either a complete visualization, a visualization corresponding to the risk of dropping out, a visualization specific to a minimal risk, or a visualization specific to academic success. A button is also available to view a detailed report to see more precisely how the success was calculated.

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.

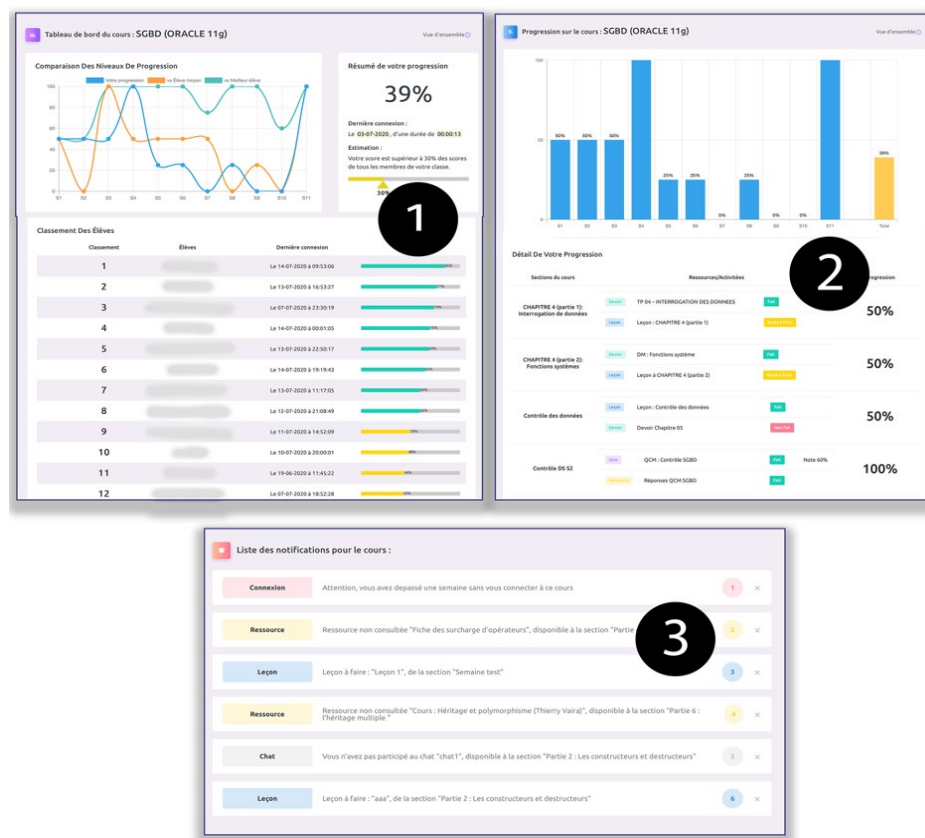


Figure 3. Full screen view of the dashboards summarizing the report for the student

The first interface (1) is divided into three parts. The first one helps the learner to situate himself/herself and to increase the learner's motivation and engagement. It 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. The second part displays the overall progress level in percentage, the date and duration of the last connection (last session) as well as an estimate of the student's ranking in relation to the other members of class. This estimate is displayed in the form of a progress bar with a three-color coding (red, yellow and green). The values of this bar are calculated based on the student's ranking. The last part shows a ranking table of all students in the class. The table includes the student full name, date and time of last connection and a column showing the overall progress level of each student. The latter is displayed as a progress bar with the same color-coding rule. 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 (blue color) summarizes the student's progress for each section of the course. The overall progress level is presented as a vertical progress bar with the same color coding as above. This same interface displays the details of the student's progress in each section. This progress detail is displayed in a table below the graph, section title, type and title of the activity/resource, with the completion status, either "done" if the activity or resource is already done (green), or "still to be done" if the activity or resource is still to be done (yellow), or "not done" if the activity or resource has not been done within the time limit planned by the teacher (red). 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. An icon in the form of a cross is used to mark the notification as read in order not to display it a second time. 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 has not been read yet, the sending is not done.

TABAT USAGE STUDY

This study aims to test TaBAT and evaluate its impact on self-regulation and prediction of success of two classes of the Higher Institute of Engineering and Business in Morocco. We present here a study based on a mixed quantitative and qualitative approach, with the aim to present the results obtained after a feedback on the use of the TaBAT tool, and then to collect the impressions and opinions of the participants. The methodology and the results analysis are presented below.

METHODOLOGY

This study is conducted on a population of 51 students (25 first-year and 26 second-year), all taking courses organized in a blended learning modality, which takes advantage of both face-to-face and online learning. Some course sections are done face-to-face, with some sections online on the Moodle 3.8 platform. First-year students took a course entitled "Object-Oriented Conception" over a 14-week period, while second-year students took a course entitled "Object-Oriented Database" over an 8-week period. Both courses were finalized with a proctored face-to-face exam. In order to respect the sanitary protocol implemented during the COVID-19 pandemic, the institute has limited the number of students to 10 to a maximum of 14 per group with no mixing between the different groups.

The first-year class is composed of 25 students divided into two groups. The first group has 13 students and the second one has 12 students. The second-year class is composed of 26 students divided into two groups of 13 students. The students of both classes are aged between 18 and 35 years. Table 1 summarizes the demographic profile of participants.

For each class, one group was exposed to the experiment of using the TaBAT (exposed group), while the second group did not have access to the dashboard to analyze learning traces (control group).

Table 1. Demographic profile of participants

	1st year	2nd year
Gender		
Male	19	18
Female	6	8
Age		
18 – 25	21	24
26 – 35	4	2
Learner initial computer skills		
Novice	2	0
Intermediate	6	3
Advanced	14	18
Expert	3	5
Computer usage time		
2 – 5 hour per day	3	6
5 – 10 hour per day	22	18
More than 10 hours per day	0	2

DATA ANALYSIS AND RESULTS

The online part of the course for the first-year students consists of 9 sections, with 7 lessons, 3 files to download, 5 URLs to visit, 2 assignments due on scheduled dates at the beginning of the course and one quiz to take. For students in the second-grade class, the online part is composed of 7 sections, with 3 lessons, 12 files to download, 2 URL links to visit, and 4 assignments due on scheduled dates. The analysis of the activity of the two classes was done using the TaBAT tool dashboards via the teacher report. Table 2 describes the result of the two experiments conducted on the two classes.

Table 2. TaBAT usage statistics

	1st year		2nd year	
	Exposed group	Control group	Exposed group	Control group
Number of active users	13	12	13	11
Cumulative time to complete the course	74 h 05 min	34 h 45 min	45 h 57 min	15 h 57 min
Average percentage progress score	70.69%	43.08%	85.54%	37.61%
% of assignments returned on time	96.15%	45.83%	44.23%	11.54%
% of assignments returned late	3.85%	0%	26.92%	15.38%
% of assignments not returned	0%	54.17%	28.85%	73.08%
Prediction of success (online success)	13/13	9/12	13/13	8/13
Effective success (validation of the face-to-face exam)	13/13	9/12	13/13	9/13

We note at first that all students in the first-class groups logged into the online course. In contrast, for the second-year class, all students in the exposed group logged into the online course. For the control group, 2 students did not take the online part of the course.

The second observation concerns the total time spent doing the online course activities. This time is represented in Table 2, cumulated for each group. For the first-year class, students in the exposed group spent more than twice as much time as those in the control group doing the online course. For

the second-year class, students in the exposed group spent almost triple the amount of time as those in the control group.

The third observation concerns the performance of the four groups, which is represented in Table 2 by the average progress score in the online course. The progress of each student represents the number of activities or resources consulted or completed divided by the number of activities or resources defined by the teacher at the beginning. The average obtained for the progression of the exposed group in the first-year class is significantly higher than that of the control group in the same class, while for the second-year class, this same average is more than twice that of the control group.

The fourth observation concerns the analysis of homework completion. For the first-year class, the exposed group had a 100% (96.15% + 3.85%) homework return rate (homework returned on time with those returned late), while for the control group, the same rate was 45.83%. For the second-year class, the exposed group had a 71.15% (44.23% + 26.92%) rate of return, while the control group had a 26.92% (11.54% + 15.38%) rate.

The final point concerns student success. In this study, the level of success calculated by the TaBAT is compared to the level of success obtained after the terminal exam. Table 2 shows that TaBAT was able to predict the totality of the success of the learners in the exposed groups in both classes. For the two control groups, the results are also encouraging, with the prediction provided by the tool being virtually similar to the face-to-face exam. This result demonstrates the effectiveness of the success algorithm, based on our theoretical e-LSAM model to predict learners' success well before the end of the online course.

DISCUSSION

Concerning the number of learners who are not connected to the online course and who are members of the control group of the second year, we can explain this by the fact that the learners of the control groups did not have the possibility to receive again the reminder notifications launched automatically by the TaBAT tool and that the contact with the teacher was done face to face. Whereas for the exposed groups, the teacher had the option (through TaBAT) to contact each learner by e-mail, which allowed for individual progress.

The increase in participation of the two control groups in the two target classes of our study gives a positive return on experience to the TaBAT tool, reflecting the contribution of this tool in helping learners resist distractions, regulate their learning and monitor their performance. The increase in participation in the course has influenced the progression of each group. Indeed, we observe a significant increase in the average progress of the exposed groups of both classes, mainly explained by the proactive actions carried out manually by the teacher or sent automatically by the TaBAT tool (proactive phase), in order to remind the learners (with the help of notifications) if they still have resources not to be consulted (file to be downloaded or URL to be visited) or activities not to be completed (lesson, homework to be handed in, quiz to be done). And let's not forget the important role of the learner's report which allows learners to self-assess and follow meta-cognitive strategies to improve their online performance.

As well as participation and progress in the online course, the number of assignments submitted has also increased for both groups exposed to the use of the TaBAT tool. This increase is mainly due to the notifications sent automatically by the tool when an assignment is due, or when there is a delay in the submission of the assignment. These notifications include the date and the number of days left to hand in the same assignment. These proactive actions were able to help learners remember the due date and have a higher submission rate than the control group.

Regarding the prediction of learner success, the TaBAT tool has proven very effective for this role. The results of the first study demonstrate the capacity of the tool to predict the success of online learners in both classes, compared to their actual success (after the face-to-face exam). These results

also show that the learners' performance and success is partly due to their ability to provide effective work at home, better preparing them for in-class tests.

QUALITATIVE STUDY

A qualitative study was conducted to understand the impact of using TaBAT on the participants of the previous study. This study is based on the impressions and opinions of the two exposed groups, to collect information to describe the motivation and attitude of the students towards the use of the TaBAT. Twenty-six learners participated in this study, all from the two exposed groups as they were able to use and test the TaBAT tool during their online courses. In the following, we present the structure of the survey with the analysis results.

SURVEY DESIGN

A questionnaire was submitted to the students who took part in the experiment to use TaBAT (26 students from both exposed groups) in order to analyze their performance in the online courses. Responses are anonymous and used for statistical purposes only. The questionnaire was presented in French and structured in two parts (see Appendix A):

- **Questions about the quality of TaBAT:** this part is where students give their opinion about their satisfaction with the visual, usability and usefulness of TaBAT;
- **Open-ended question:** regarding visual elements (graphs or indicators) that students can possibly propose to modify or integrate into TaBAT.

This questionnaire focuses on the students' opinions on several aspects: their perception of the graphical representation, the representation of the information, and the usability and usefulness of the proposed dashboards, their overall satisfaction with the experience, as well as their feelings about the impact of the tool on their degree of self-regulation and final success. The questionnaire was adopted from recent work (Hauer et al., 2018; Park & Jo, 2019), on the use of learning analytics dashboards as a decision support tool.

RESULTS OF THE SURVEY

This qualitative analysis will give feedback from the students on the aspects presented before (visual/information, usability, satisfaction, self-regulation and academic success). It will also be a way to validate the results obtained in the first study.

The level of students' appreciation about the visual and the representation of information on the TaBAT is presented in Figure 4 (in blue): 52% of the students appreciated with an evaluation "Strongly agree", 29% of students agreed with the visual and the representation of data, while 17% were neutral in their expectations, while only 2% appreciated less the visual and the representation of data and found difficulties to interpret all the information contained in the dashboard. This same figure presents (in orange) the appreciation level about the usability (accessible and easy to use without help) of TaBAT, where half of the students felt that the tool was always accessible and that its use was very easy, 37% felt that the tool was accessible and that its use was easy, 10% were neutral in their expectations, and 8% of the students felt that it needed more instructions from the instructor to use it easily.

Regarding the students' level of evaluation about their understanding of the tool's usefulness (presented in Figure 5 in blue), 62% of the students stated that they completely understood the usefulness of the tool, 33% reported that they understood the usefulness of the tool and its functionalities, 4% were neutral in their expectations, and 2% of the students found that they needed more explanation in order to understand the tool's usefulness. For students' level of satisfaction with their first use of the TaBAT (in orange), 64% of students were very satisfied with their use and recommend it

favorably, 36% reported being satisfied with an “Agree” evaluation, and no subjects reported being dissatisfied with their use of TaBAT.

Regarding the impact of tool usage on students’ performance and self-regulation (presented in Figure 6 in blue), 49% felt that TaBAT helped motivate them more to adapt autonomous behavior, encouraging them to study more effectively and to change their learning behaviors, 38% felt that the tool contributed little to changing their behaviors in order to achieve the learning objectives, and 13% were neutral in their response. When asked to evaluate the impact of TaBAT usage on students’ academic success, 65% felt that the use of the tool improved their performance in the course, thus improving their academic performance, 27% indicated that the use of the tool had little impact on their academic performance, and 8% were neutral in their perceptions.

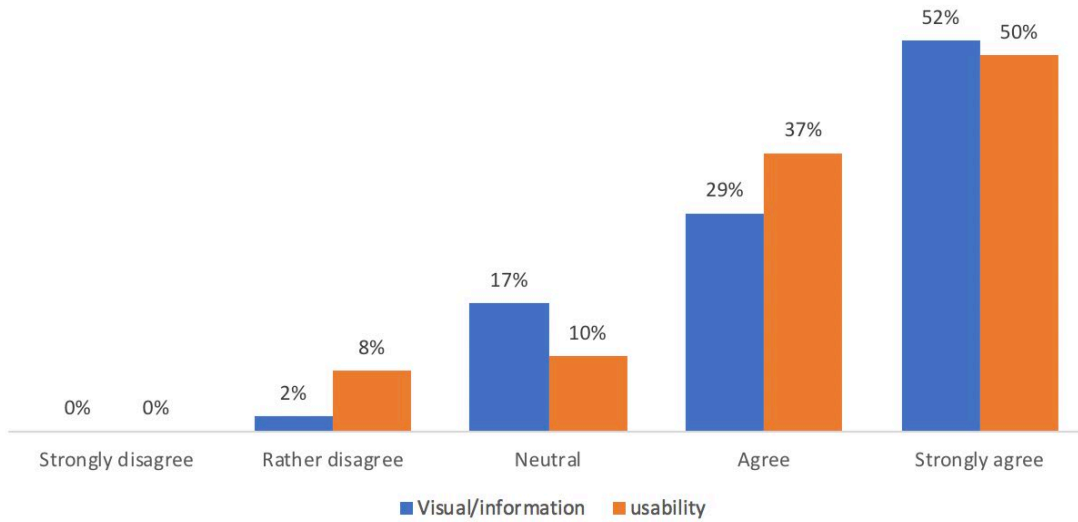


Figure 4. Appreciation level on visual/information and usability

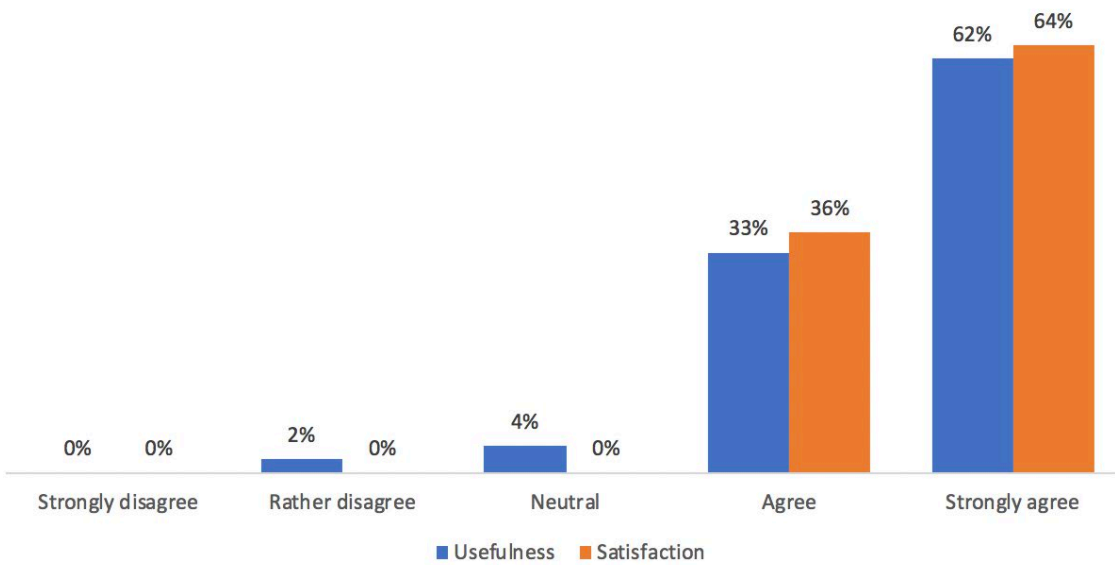


Figure 5. Appreciation level on usefulness and satisfaction

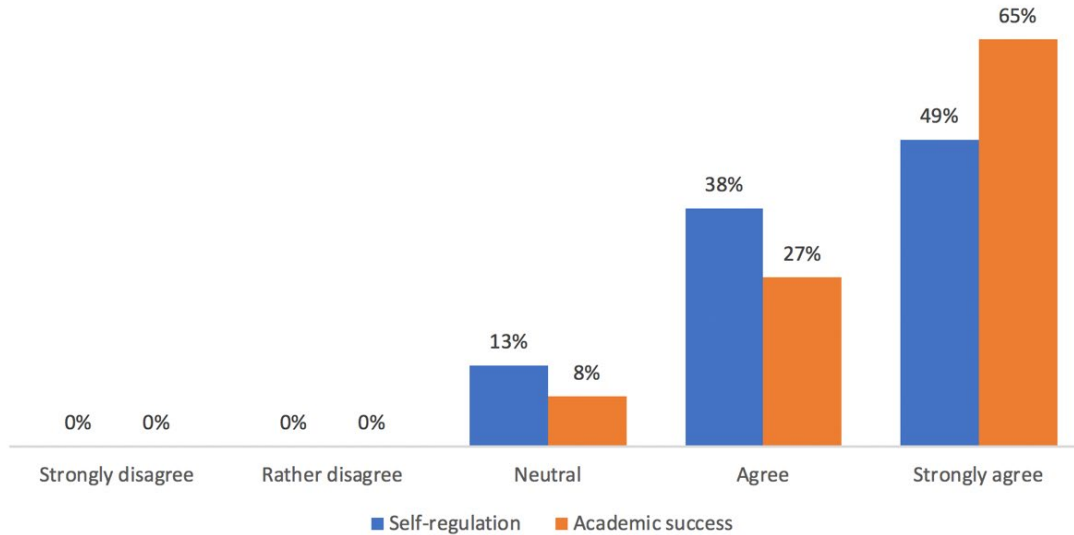


Figure 6. Evaluation of TaBAT's impact on self-regulation and academic success

Note that we also asked an open-ended question to allow students to propose additional visual elements (graphics or indicators) to be integrated into TaBAT. Two students made a proposal. The first one proposed to change the background color and to choose more attractive colors, the second one proposed to generalize the use of TaBAT to other courses.

DISCUSSION

The purpose of this second study was to verify and support the results obtained in the first study regarding the usage of TaBAT. We note that the students in both groups reported that they appreciated the visual representation and data representation offered by the tool. They found it accessible, useful and easy to use. All the students were satisfied with the usage of the TaBAT, they also felt that the tool made them more autonomous, motivated and had an impact on their academic success.

These opinions from the participants allow us to have a first feedback on the visualization of a learning dashboard. They demonstrate the ability of our tool to display key indicators with different visualization means depending on the user's role, as well as to encourage learners to track their progress and self-regulate.

CONCLUSION AND LIMITATIONS

In an attempt to reduce the dropout rate of learners, and at the same time to improve their success in online courses, we have proposed in this article a first study that presents the development of a tool that can analyze learning traces and represent them in the form of dashboards for teachers and learners. The main LMSs do not really allow the teacher to effectively monitor the information available; the proposed tool allows teachers and learners to visualize different educational indicators in order to control the learning process. Two studies were conducted: first, to test the effectiveness of the tool in analyzing learning traces in online courses planned by an engineering school in Morocco; and second, to collect feedback from the participants of the first study. The results of these two studies finally confirmed that the use of the tool allowed to increase the learners' performance, to improve their autonomy, and finally to improve their academic success.

This first study has some limitations, the first being the small number of participants. In fact, this study is limited to two classes, the inclusion of multiple classes in the study would require more important resources. Due to this sample size limitation, more extensive statistical analyses were not

conducted. Finally, because the tool is being recently developed as external to LMSs, testing in other organizations within the private or public education sector would require authorization and logistical work. However, these first results are very encouraging and will have to be confirmed in the future with larger studies.

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APPENDIX. QUALITATIVE STUDY SURVEY ON TABAT USAGE

Part 1: Questions about the quality of TaBAT

	Questions	Strongly disagree	Rather Disagree	Neutral	Agree	Strongly agree
Visual/information	Visual elements of tool are arranged for quick perception?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool includes appropriate graphic representations?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool displays the information correctly on both desktop and mobile devices?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Information is provided in a concise, direct, and clear way?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Usability	Tool is easy to access?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool was accessible when I needed it?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	I was able to use the tool without much effort?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	I knew how to use the tool without the instructor's advice?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Usefulness	I consider the tool useful?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	It is useful to compare my performance to other learners?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	The notifications provided by the tool are useful to monitor my progress?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	It is useful to use the tool to monitor my performance improvement?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Satisfaction	I would like to use the tool again for another course?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	I am satisfied with the different visual elements provided by the tool?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	I recommend the usage of the tool for pedagogical purposes?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Self-regulation	Tool allowed me to better assess my performance relative to others?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool encourages me to be reflective about my previous learning behavior?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool motivates me to adapt my learning behavior if necessary?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool motivates me to study more effectively?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	I am able to evaluate my individual performance easily through the dashboard?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool allowed me to monitor my own learning process in a coherent way?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

	Questions	Strongly disagree	Rather Disagree	Neutral	Agree	Strongly agree
	Tool encourage me to change my learning behavior?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool helped me achieve my learning goals?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Academic success	Information displayed through the tool has helped me to improve my performance in the course?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool has improved my academic performance?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	Tool motivate me to complete my online learning?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Part 2: open-ended question

In order to express your preferences on your usage of the TaBAT tool, do you have other visual elements (graphs or indicators) that you would like to integrate?

Yes No

If yes, what are these elements?

.....

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