Explainable Learning Analytics Dashboard: Enhancing Understanding of Insights derived from Educational Data

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Abstract

The integration of Learning Analytics into educa- tional environments can improve the learning process. However, to be used effectively, these tools need to be both explainable and comprehensible. This article introduces a novel dashboard known as the Explainable Learning Analytics Dashboard (EX-LAD), designed to present learning analytics data relating to student performance, engagement, and perseverance in a clear and accessible way. The main aim of this study is to make this information easily understandable for both teachers and students, even for those without in- depth knowledge of data analysis. The EX-LAD primarily empowers students to self- assess by tracking their progress. This enables them to better target their weaknesses and try to remedy them quickly and effectively, thus avoiding any risk of failure. Teachers, meanwhile, can identify students' specific needs, and detect any learning difficulties. By emphasizing explicability, we aim to boost user confidence in the analyses generated by the system and encourage their engagement in the process of continuous improvement of the educational experience. To showcase the effectiveness of our dashboard, we conducted a case study using real data collected from ESIEE-IT, an engineering school in France, during the 2021-2022 academic year .

Key Words: Explainable Learning Analytics, Dash- board, Higher Education

1 Introduction

During the COVID-19 pandemic, distance learning systems emerged as a crucial means of ensuring teaching continuity in a virtual environment provided by the World Wide Web. Despite initial reservations, teachers and students have widely adopted these e-learning solutions. Today, while the situation has improved and allowed a return to the classroom, many higher education institutions still wish to maintain certain aspects of distance learning [1], particularly by leverag- ing Learning Management Systems (LMS). LMSs are commonly used in institutional academic environments to deliver educational content and enhance the learning experience of teachers and students. However, it is important to note that there are many LMSs available on the market, such as Moodle, widely used in univer- sities, and BlackBoard Learn [2], which is of interest in our study. Although these platforms provide learning analytics dashboards to showcase valuable information, they often face two significant challenges. Firstly, they tend to prioritize student performance which measures the students's level of achievement, their ability to assimilate knowledge and demonstrate academic skills, as well as their positioning with regard to their peers in terms of academic results [3], [4] such as grades obtained in various activities, exams, projects, presentations etc. Regrettably, this narrow perspective often neglects other vital indicators like engagement encompassing cognitive, behavioral, social, and emotional aspects.

- Behavioral engagement refers to students' consistent presence and dedication to diverse learning activities. It is expressed through assiduous participation in class, where students ask questions, interact with learning materials, and contribute constructively to discussions.
- Cognitive engagement showcases the students' active mental involvement, going beyond simple physical presence. It embraces creativity, critical analysis of information and problem-solving, reflecting a deep investment in the learning process.
- Social engagement manifests through students' social interactions within their educational environment, as well as through their participation in collaborative activities. It goes beyond the boundaries of academic learning, fostering a sense of connection and belong- ing among learners.
- Emotional engagement refers to the students' emo- tional desire, motivation and satisfaction during the course (enthusiasm, feeling of being valued). It can be perceived by the student's interest in the course and his/her relationships with classmates and teachers. As a result, there is a pressing need for a more com- prehensive approach that takes into consideration the multiple dimensions of students' learning and provides a holistic view of their educational experience. Another challenge that arises when using analytical dashboards is that users, including teachers and students, may not necessarily have in-depth knowledge of data analy- sis. Dashboards with complex

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and hard-to-understand graphs can result in either limited future usage of these tools or incorrect interpretation of the data. This can lead to erroneous conclusions or unfortunate interventions. Visualization techniques in general, and Learning Analytics Dashboards (LADs) in particular, have proved effective in visually communicating the data. Visualization techniques are used to graphically represent data that appears complex to simplify it and make it more comprehensible to users.They also enable results to be communicated clearly and effectivelyto a varied audience, relationships and trends to be identified, and decision-making to be supported. There are several types of visualization, the most common of which are as follows: bar charts and histograms, often used for comparisons between categories; pie charts, used to represent proportions or parts of a whole; and scatter plots, used to present relationships between several variables etc. However, they are often considered difficult to understand and interpret [5]. To address this thinking, a new field called "Explainable Learning Analytics " [6,7],has been introduced. Therefore, our research questions are the following:

• RQ1: What indicators are essential for supporting both students and teachers in utilizing LMS effec- tively?

• RQ2: How can we create a Learning Analytics dashboard that is understandable and interpretable for individuals without expertise in data analysis? To address these research questions, we developed an EXplainable Learning Analytics Dashboard (EX- LAD) that presents learning analytics data on stu-dent performance, engagement, and perseverance in a clear and easily understandable manner.The objective of EX- LAD is to make this information accessible not only to teachers but also to students, who may not have extensive knowledge in data analysis. This dashboard empowers teachers to gain valuable insights into their students' progress, identify at-risk learners, and provide targeted support. Similarly, students can utilize this dashboard to track their learning journey, identify strengths and weaknesses, and make informed

decisions to enhance their academic performance. To demonstrate the effectiveness of our dashboard, we conducted a case study using real data collected from ESIEE-IT, an engineering school in France, throughout the academic year 2021-2022. This case study serves as concrete evidence of the impact and value our dashboard brings to the educational context.The paperis organized as follows: Section 2 presents a review of some recent learning analytics dashboards in higher education. Section 3 describes the proposed EX-LAD. Section 4 illustrates our approach by providing answers to the research questions, section 5 discusses the results obtained in our study and finally, section 6 concludes our work and presents our future works.

2 Related Work

In this paper, we focus on the usefulness of learning analytics dashboards for monitoring students and de- tecting the risk of failure or drop-out. In this context, we considered various research works for our literature review, including those from the Learning Analytics (LA) and Educational Data Mining (EDM) commu- nities. We conducted keywords-based queries such as 'learning analytics', 'dashboard', 'learner', 'Indicators', 'online learning environment', and 'data visualization' while specifying the research area, higher education. We discarded articles published before 2019 as we wanted to focus on recent works. These keyword-based queries returned over 670 research articles. We read their abstracts and selected those that presented empir- ical research on Learning Analytics in higher education all over the world. We excluded review articles and theoretical articles that focus on the Learning Analytics Dashboards aspects. Following this methodology, we finally selected nine papers that we analyzed in depth. In [8], the authors introduce the 'TELA system,' a Learning Analytics dashboard designed to enhancethe performance and engagement of students enrolled in distance learning courses.Its primary goal is to simulate students' motivation to continue their studies by providing them with the opportunity to monitor their progress and grade evolution while comparing their performance with that of their peers. To achieve this objective, the system offers a diverse range of learning indicators, including measures of engagement such as cognitive engagement, assessed by the number of activities completed and resources accessed by the student; behavioral engagement, determined by the frequency of interactions; and social engagement, calcu-lated based on the volume of messages exchanged in dis- cussion forums. Additionally, the system incorporates performance metrics derived from students' grades. In [9], the authors not only provide a descriptive

overview of the results but also expand their perspec- tive to include predictive and prescriptive elements.The objective is to enhance student engagement byoffering detailed explanations of predictions for each learner.This dashboard specifically focuses on a critical aspect of engagement: cognitive engagement, inferred from students' resource usage, along with academic performance, assessed through each student's GPA (Grade Point Average). By incorporating these pre- dictive and prescriptive features, the dashboard aims to give students a proactive outlook on their learning, encouraging them to optimize their academic success. 'Tabat' [10], is a Learning Analytics dashboard designedfor both educators and students. It offers an in-depthanalysis of learning data, aiming to simplify monitoringand control of the learning process.Their main objectiveis to use this tool to enhance the engagement andsuccess rates of online learners. The 'PLD prescriptive dashboard' [11] guides students in improving their academic performance. It aims at presenting students with a variety of learning indicators such as behavioral engagement, cognitive and social engagement as well as a performance indicator calculated from the students' grades. These indicators are grouped by type and each page is dedicated to a specific type of indicators. This dashboard offers personalized recommendations for each student depending on the difficulties he/she faces and clusters students who share the same learning behavior into different profiles. The dashboard introduced in [12] diverges from typical daily dashboards by adopting a personalized learning support approach. It focuses on face-to-face interac- tions, with particular emphasis on collaborative ar- gumentation between students.This platform enables teachers to identify groups of students facing similar argumentation difficulties, by providing exclusively so- cial engagement indicators. The dashboard presented in [13]is specifically dedicated to teachers entered around behavioral engagement and performance indicators. Its primary goal is to offer behavioral process-oriented feedback in online courses.The visualizations are brought together in an interface, offering a global view of the indicators. The authors in [14] developed a Learning Analyt- ics dashboard that allows students to evaluate their cognitive engagement as well as their performance and influences their motivation in distance learning environments. This dashboard offers a global view of these indicators by grouping visualizations in one inter- face which facilitates interpretations.It also generates personalized messages for each student according to their weekly report. The authors in [15] dedicate their dashboard only to students. It offers a single type of visualizations, i.e. a progress bar showing the student's grade for each notion

of the course and using only one learning indicator which is performance calculated using grades, number of correct answers and question response time. This dashboard also recommends resources for each chapter of the course that can help the student having a problem in this chapter. Finally, the dashboard developed in [16] proposes a learning analytics approach, known as 'Student In- spection Facilitator (SIF)'. It assists instructors in identifying students requiring special attention based on their numerical data. SIF could be integrated into institutional systems to effectively interpret student be- havior and classify them for intervention, while leaving the choice of whether to intervene to the instructor. We established a set of criteria for comparing various existing works in the field. This methodology allows us to conduct a thorough analysis and discern the strengths and weaknesses inherent in each approach. Table 1 provides a summary of the chosen studies based on five primary criteria: (a) target users, (b) data protection, (c) learning indicators, (d) visualization, and (e) actionable insights: a) Target users (TU) represent the final users of the dashboard who can be students (S) and/or teachers(T). This is an important criterion, since it guar- antees the dashboard's relevance and usefulness to those who need it.By defining the dashboard's end- users, we can customize and design it to meet their specific needs and identify the indicators that aremost relevant to them. b) Data protection (DP) indicates whether the researchers have guaranteed the ethical use of data by teachers and the educational team as the col- lected data raises legitimate concerns about con- fidentiality and privacy. We therefore proposed rigorous measures to ensure data integrity and security in line with the General Data Protection Regulation (GDPR), highlighting four fundamental requirements which are (R1) data confidentiality, (R2) informed Consent, (R3) data Anonymization, (R4) transparency and (R5) diversity.

• Data confidentiality requirement aims to ensure the protection of the information of users partic- ipating in the study, in compliance with the rules established by the (GDPR). It aims to minimize any potential risk of disclosure of sensitive data. • Informed consent requirement ensures that par- ticipants are provided with transparent infor- mation on the final use of their data, thereby guaranteeing their consent and agreement to the use of their data and fostering the establishment of a relationship of trust. • Data anonymization requirement aims to remove all personal information that could identify indi- viduals and reveal their identity, giving absolute priority to the protection of privacy. • Transparency requirement emphasizes the trans- parency of the experimental results obtained, as well as the explicability and comprehensibility of the approach used by the participants to foster mutual trust. • Diversity requirement ensures the inclusion of di- verse data representing a variety of demographic, social and cultural groups. c) Learning Indicators represent the specific type of indicators used in the dashboard that may include performance indicators (P), cognitive en- gagement indicators (CE), behavioral engagement indicators (BE), social engagement indicators (SE), and more.We proposed this comparison criterion based on our first research question. d) Visualization is described based on three main criteria which are: (i) Number of visualizations and chosen techniques, (ii) explainability and (iii) objective of visualization referring to our second research question. This criterion is proposed con- sidering the importance of visualization techniques in a dashboard, as previously highlighted, as well as their ability to simplify the presentation of information for different users.

• Number of visualizations and type:This crite- rion focuses on the variety of the visualizations proposed in the dashboard (for example scat- ter plots, bar charts, pie charts, etc.). • Explainability:This criterion assesses whether the provided visualizations are understandable and easy to interpret by non-experts in data analysis.It can be achieved either by offering an explanatory text, meaningful color coding such as traffic code colors, or through the number of proposed interfaces. • Objective of visualization:This criterion presents the idea that each visualization aims to convey to the user. It could include showing change over time (temporary evolution), comparing group values (comparison), establishing relationships between variables, or displaying value distributions.

e) Insightful Actions represent the types of actions delivered to the users of the dashboard following the visualizations such as personalized recommenda- tions or notifications. These recommendations are designed to support learners on their learning path

by providing personalized support and advice tai- lored to their individual needs. For instance, they may include pedagogical suggestions like proposing specific activities or resources to students, as well as personalized learning path recommendations that adjust to individual student needs. Notifications within learning analytics dashboards play a crucial role as well, delivering pertinent information to diverse users and enhancing their interaction with the tool. They empower learners to actively en- gage with their studies, offering updates on course progress and various activities to help them monitor their advancement. Notifications also stimulate so- cial engagement by alerting users to new group dis- cussions, fostering active participation, and encour- age behavioral engagement by reminding students of impending activity deadlines to ensure timely assignment submissions. Additionally, teachers can benefit from notifications that highlight any issues with a student, aiding in the identification of those at risk.

Based on the works we studied, we made some observations. First, we observe that all of the studies uses the performance indicator, which is derived from student grades (see [17]) except [12]. We also note a diversity in the proposed engagement indicators. For example, works [8], [9], [10] and [14] focus on cognitive engagement, while learning analytics dashboards in [8], [10], [11], [13] and [16] deal with behavioral engagement, and [8], [10], [11] and [12] address social engagement. Most of these works are limited to two indicators, namely performance and an engagement indicator, ex- cept for [8] and [10], which combines all four indicators. However, most studies opted for a straightforward pre- sentation of data in the form of visualizations, without developing the formulas for calculating indicators or clearly identifying engagement and performance. One exception is [10], which developes several scores to facilitate the understanding of each indicator. Among these scores, we may find the participation score, which is calculated according to the duration of interaction with the platform, thus reflecting the student's behavioral engagement. Another score, called the section progress score, indicates each student's level of progress in each section of the course. They also offer the Course Progress Score, which reflects overall progress in the course. We also find the social interac- tion score, calculated from messages exchanged between students. Finally, there's the Successful Progress Score, which provides an estimate of the learner's level of success. Nevertheless, although several different learning in- dicators were proposed, visualization options remain limited. Most studies rely mainly on bar charts, curves,

Table 1: **Comparative table between existing learning analytics dashboards.**

Ref	TU	DP	Learning Indicators				Visualizations			Actions
			P	BE	SE	CE	Number& Type	Explainability	Objective	
[8]	S	√	√	√	√	√	5 Bar charts, 1 Lin- ear Graph, 5 Line charts, 1 Gauges, 1 Tree graph	×	Comparison, Evolution	×
[9]	S	√	√	×	×	√	5 Line charts, 1 histogram	Text	Evolution	×
[10]	S/T	√	√	√	√	√	6 Tables,3 Line charts, 1 Bar chart, 1 Pie chart	×	Comparison, Evolution	Notifications
[11]	S	√	√	√	√	×	2 Bar charts,1 Gauge, 1 chart, 2 Lin e Colum n charts	×	Comparison	Recommendations
[12]	S/T	√	×	×	√	×	1 Radar chart, 1 Network Graph, 1 Bar chart	Text, Color Coding	Data distribu- tion	×
[13]	T	√	√	√	×	×	2 Bar charts,3 Ta- bles	Color Coding	Data distribu- tion	×
[14]	S	√	√	×	×	√	1 Pie chart, 1 List, 1 Table	×	Data distribu- tion	×
[15]	S	√	√	×	×	×	1 Radar chart, 1 List, 1 Scatter Plot	×	Data distribu- tion, Evolution	Recommendations
[16]	T	√	√	√	×	×	Radar charts, 2 box plots	Text Color Coding	Data distribu- tion	Recommendations

Target Users (TU), Data Protection (DP), Students (S), Teachers (T), (√)Yes, (×) No

or even tables and lists. These visualizations are not suitable for handling complex information, as they may not capture all nuances and complexities effectively. In addition, they are not suitable for the comparison of multiple variables, which can restrict the depth of analysis and lead to misinterpretation. A few exceptions, however, introduce scatter and radar plots, as referenced in articles [15], [12] and [16]. It is observed that the works presented do not pay particu- lar attention to the comprehensibility or explicability of their visualizations. Given the limited choice of available visualizations, there is a risk that users will find it difficult to understand the presented results. However, we note a few exceptions, notably in works [9], [12] and [16], where text descriptions are provided, and sometimes significant color choices were used, such as traffic light colors in works [12], [13] and [16]. Finally, it is important to note that only three studies provide their users with insightful actions. [15], [11]and [16] deliver personalized recommendations to the students using their dashboards and [10]'s dashboard as well offered notifications to the students for each indicator allowing them to identify their strengths and weaknesses and make informed decisions to improve their academic performance. To guarantee these ob- jectives, we place great emphasis on clarity, providing visualizations that are easily understood by all users, accompanied by explanatory text for the indicators

presented. Our solution also respects privacy and ensures the protection of the personal data used. To propose adequate support actions, we suggest different profiles of students based on the learning indicators that will be defined later. Another observation is that the presented learning ana- lytics dashboards share an important common feature: the protection of the data used in their visualizations. The authors ensured the data used is anonymized to respect ethical requirements and preserve the privacy of the concerned individuals but there is no indication that the other requirements were respected. In the next section, we describe our proposed EXplain- able Learning Analytics Dashboard EX-LAD.

3 The proposed EX-LAD

In this section, we introduce the participants in our study, describe our case study in detail to demonstrate the effectiveness of our approach and finally present the steps of our proposed Learning analytics dashboard.

3.1 Study Context

We conducted a case study with real data collected from the LMS used by an IT school called ESIEE- IT [18] . ESIEE-IT is based in France. It offers several computer science programs of different specialties such

as artificial intelligence, cybersecurity, and information systems dedicated to different student profiles such as bachelor, engineer, and master. The participants in this study were 128 students who took a programming course with Python. Among these students, 22 were enrolled in Master Green, 48 took an engineering course, 29 BTS and 29 following a Master in Big Data. There were 117 males and 11 female students participating in this study. The dataset was collected during the 2021-2022 academic year. While collecting these data, we proceeded to data anonymization to ensure that it could be used in accordance with ethical principles.

The Python programming course is taught in a hybrid way, i.e., 80% of the course time is online and 20% of the course time is face-to-face. In practice, during online lessons, the student must follow the course through the LMS of the school which is Blackboard Learn [2]. During the face-to-face session, the student must be present at school to interact with teachers and ask questions related to the course. The course on Blackboard is composed of a set of sequences. Each sequence can contain four types of resources which are the following:

- (a) the course in a video format,

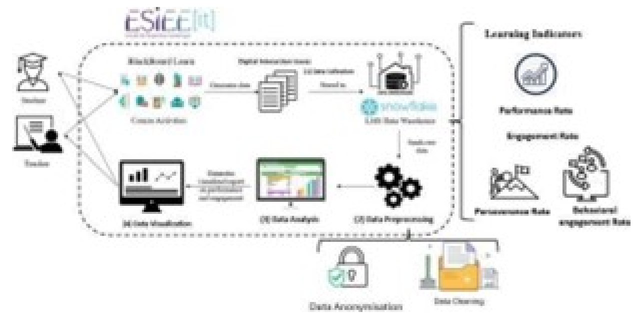
- (b) the notes allowing the student to constitute exploitable resources in different formats such as text, video or audio that can be used in addition to the course,

- (c) the documents containing instructions for the exercises along with corrections either as an attach- ment or directly in the document,

- (d) the quizzes composed of 5 to 10 questions deliv- ered as assessment activities and a final test made of 20 questions. Student interactions with Black- Board Learn [2] were recorded in the Snowflake data warehouse. These interactions include data such as number of clicks, time spent on the plat- form, number of accesses to the platform, and other information that will be detailed later. In the following section, we present the different steps of our dashboard.

3.2 Steps of the proposed EX-LAD

In this section, we present the four steps of our solution for our dashboard which are: data collection, data pre-processing, data analysis and data visualization as shown in Figure 1.



3.2.1 Step 1. Data collection

In the first step, we collected digital learning traces resulting from the learner's interactions and stored in the SnowFlake data warehouse. Our dataset contains 128 instances and 106 features of the student .Table 2 describes these different features. It is made up of 26 features organized into five groups describing the various features of our dataset.

The first group includes the student's personal data (SF) which is name (1), e-mail address (2) , public (3) and course of study (4). The second part (AF) from feature number 5 to 8 is related to the student's access to the platform, such as 'Course Access Connection' and 'Course Access Minutes'. The following part from 9 to 18 (PF) concerns academic performance, including grades, ranks and average score. Engagement indicators (EF) are described in the next section (from 19 to 25):

$$\text{performance} = 0.5 \times \text{Average}(Q_1, Q_2, \ldots, Q_n) + 0.5 \times \text{Final Score} \quad (1)$$

A student is considered successful if his or her average exceeds 50 and failing if it does not. we must mention

Table 2: **Dataset Features.**

Cat	FN	Feature Name	Type	Feature Meaning	Value Example
SF	1	Student	O	The student's name and last name	TOTO TATA
	2	Email	O	The student's academic email address	TOTO.TATA @edu.esiee-it.fr
	3	Public	O	Level and branch of studies	M2I, IA
	4	Course Name	O	The name of the course	Python
AF	5	Course Access Connection	I	The number of accesses to the course	10
	6	Course Access Minutes	I	The access time to the course in minutes	662
	7	First _Course _Access	T	First access to the course	2021_10_18 05:38:56
	8	Last _Course _Access	T	Last access to the course	2021_02_09 2:23:25
PF	9	Rating SiQ1	F	Score of quiz n° 1 in the sequence number 1	80
	10	Rank _SiQ1	I	Rank of the student in the quiz n°1 in the sequence number I	6
	11	Diff_Rating_ SjQ1	F	The difference of score between the actual quiz in the actual sequence and the last one	20
	12	Diff_Ranking_ SjQ1	I	The difference of rank of the student between the actual executable activity in the actual sequence number j and the last one	-5
	13	Rating Final Exam	F	Score of the final exam	75
	14	Rank Final Exam	I	Rank of the student in the final exam	3
	15	Diff_ Rating_ Final Exam	F	The difference of score between the final exam and the last executable activity	-20
	16	Diff Ranking Final Exam	I	The difference of rank of the student between the final exam and the last executable activity	23
	17	Avg Rating	F	The average score in all executable activities	38,75
	18	Rank	I	The rank of the student in the class	20
EF	19	SiQ1 Exe Submission Count	I	Number of attempts in the executable activity Quiz number 1 of the sequence number I	2
	20	FE Exe Submission Count	I	Number of attempts in the final exam	1
	21	T Exe Submission Count	I	Total number of attempts in quizzes	10
	22	Interaction Oriented Investment (IoI)	F	A score that measures the interaction-oriented investment of the student in all the executable and non-executable activities	37,5
	23	Course Access Connection Oriented Investment (CACOoI)	F	A score that measures the investment of the student related to the access count to the course	32,95
	24	Course Access Count Oriented Investment (CACoI)	F	A score that measures the investment of the student related to the time spent in the course	23,66
	25	Engagement	F	The average of the four investment scores to measure the engagement of the student	66,84
DF	26	Difficulty	O	Type of difficulties of each student depending on the calculated scores.	E+P+, E+P-, E- P+ E-P-

Cat: Category, FN: Feature Number, T: type, O: object, I: integer, F: float, T: timestamp, i=1..10and j=1..10

that there are two types of activities in Blackboard: non-executable activities which are the resources offered to students (pdf, video, etc.) and executable activities (quizzes, exams, etc.). The Engagement is defined as 'the active involvement of learners in a learning activity and any interaction

• Interaction oriented investment (IOI): This learning indicator aims to evaluate student engagement by considering the number of interac- tions with the LMS, compared to the most active student. It should be noted that on the BlackBoard platform, an interaction refers to the number of clicks done by the student throughout the course executable activities (quizzes, exams) and non- executable activities (consultation of documents or videos). It is calculated as follows:

$$\text{IOI} = \frac{\text{Total number of interactions for each student}}{\text{Max number of interactions for a student in the class}} \tag{2}$$

• Course Access Connection Oriented Investment (CACOoI): This indicator assesses students' behavioral engagement, focusing particularly on the amount of time they spend on the platform, compared with the most active student on the platform. This measure provides a better understanding of students' level of involvement and interaction with the resources and activities offered online. It is calculated as follows:

$$\text{CACOI} = \frac{\text{Time spent on the platform by the student}}{\text{Max time spent on the platform by a student in the class}} \tag{3}$$

• Course Access Count Oriented Investment (CACoI) : This indicator assesses student attendance by calculating the frequency of their connections to the platform, comparing them with those of the most assiduous student. This measure highlights students' level of presence and engagement in their online activities, offering valuable insight into their involvement in the learning process.It is defined as follows:

$$\text{CACOI} = \frac{\text{Total number of connections of the student}}{\text{Max number of connections per student in the class}} \tag{4}$$

It should be noted that on Blackboard, students had the option of retaking their quiz before submitting it in order to improve their results. However, this indicator is primarily designed to assess learners with mediocre results, to find out whether they really made an effort to improve their scores, or whether they were satisfied with a single attempt, which could reflect their level of motivation and commitment .On the other hand, a low perseverance value for a student who succeeded brilliantly on his first attempt should not be interpreted as a sign of disengagement. Instead, it could be a sign of course understanding and self-confidence. In our case study, the only data available regarding the three scores defined above is the overall number of clicks of connections and connection time over the whole course:we do not have the value over time and this is one of the limitations of our dashboard can only be based on the raw data collected from the LMS.on the other hand, we could connect the number of attempts a student made for each quiz during the course we refer to this indicator as the perseverance score and may analyze it during the course.

• Perseverance refers to the number of submissions to each quiz during the course.

3.2.2 Step 2. Data preprocessing

In this step we prepare the raw data for the following steps which are analysis and visualization. As our data was collected from different tables and stored in a single dataset, we have proceeded to cleaning incorrect and mislabeled data. We removed incomplete and duplicate data from our dataset to avoid false results that lead to false conclusions.Then we replaced NAN(Not a Numeric) and NaT(Not a Time) values by "0" to ensure data compatibility with numerical calculations. Finally, we have ensured that our data is anonymized in compliance with the requirements of the General Data Protection Regulation (GDPR).we eliminated all the information that could help identify the participant such as his/her email address or his/her name.

3.2.3 Step 3. Data visualization

We proposed in our dashboard a set of visualizations that meet certain criteria and offer a set of features asshown in table 3. This table explains how we presented the indicators that we calculated. We used variousforms of presentation, including raw data (scores, ranks, etc.) and indicators grouped together in graphs to provide an overview. We used various types of graphs, such as bar charts and line graphs, to show the temporal evolution of data and make comparisons between different indicators such as engagement indicators in grouped bar charts as shown in table 3. We also used scatter diagrams to show relationships between variables like the scatter plots that show evolution of student's profiles through the quizzes. The choice of chart types was made with the target audience and clarity of presentation in mind. We also ensured that our graphs were explainable, i.e., easy to interpret by a normal dashboard user and does not require any knowledge in the field of data science. We provided text descriptions for some charts like the radar charts (see table 3) and used color coding to express the level of severity of situations. In short, we developed a dashboard that is practical, user-friendly, and easy to understand by all stakeholders. In the following section, we present the actions to be taken from this dashboard.

3.2.4 Step 4. Insightful actions

The main goal of Learning Analytics dashboards is to offer different stakeholders actionable insights. Our dashboard provides clear information to students and teachers so that they can take suitable actions. The student can compare his individual level to the level of the whole class in real time and catch up. The dashboard also allows teachers to identify the students who share the same learning behavior and face the same difficulties to provide them with adequate assistance according to their specific needs. We grouped the students into four profiles based on the perseverance score noted E for engagement and performance rate that we defined previously:

• Profile 1 (E+P+): The student has a high engagement score (above the median value of the class) with a positive performance, which means that this student succeeds through hard work. He/she seems to be invested in these studies and makes a remarkable effort to get good grades. The teacher can detect potential problems by providing special follow-up to students belonging to this category.

• Profile 2 (E-P+): The student has a positive performance score and a low engagement score. This student easily succeeds the quizzes as he/she can have a good mark even from the first attempt. This means that this student does not require special help as there is no risk of failure currently. However, it is important to monitor whether this student remains sufficiently stimulated his/her studies to avoid boredom or disinterest.

• Profile 3 (E+P-): The student belonging to this category, has a low performance score despite his high engagement. This student is really dedicated to his studies, but he/she fails despite his/her efforts, therefore needs academic support in the topics in which he has difficulties.

• Profile 4 (E-P-): The student belonging to this profile has serious problems related to both perfor- mance and engagement. This leads us to conclude that the student may be disinterested because of problems related to the course itself which affects his results or because of external factors which may be psychological problems, family, or a bad choice of academic program. A quick intervention is then needed to avoid the risk of dropping out. In the following section, we present the different dash- board interfaces.

4 Experimental Results

In this section, we present the experimental results, which we have organized according to the research questions they answer.

• RQ1: What are the necessary indicators to support students and teachers when using LMS? To answer our first research question, we present how we displayed the learning indicators in our dashboard for both students and teachers. To assess student performance, we choose grouped bar charts. These diagrams illustrate the evolution of the student's grades throughout the course, from the quizzes to the final exam. They enable the student to compare his or her grades with the best and lowest marks obtained. In this way, students can see where they stand in relation to their classmates. The grouped bar charts presented in Figure 2 show the evolution of Student 7's grades through the course. We notice that this student managed to get consistently good scores for the first 4 quizzes but then suddenly he/ she had zeros for the following five quizzes (quizzes 5,6,7,8,9) which means that he/ she is no longer performant and that he/she has serious problems knowing that

Table 3: Visualizations of EX-LAD and their distinctive characteristics.

LA indicators / Data	Visual Charts	Comparative data	Objective	Explainability
Student's ranks	Bar chart	Individual and class scores	Comparison, Temporal evolution	None
Student's grades	Bar chart			Color coding
Ranks and grades	Bar chart			None
Perseverance score	Bar chart combined with line chart	Individual values and class median	Comparison Temporal evolution	None
	Bar chart	Compared with grades	Comparison Temporal evolution	Text
Engagement indicators (IOI, CACOoI, CACoI)	Grouped bar charts	Individual and class scores.	Comparison	Text
Performance	Bar chart	Individual and class scores	Comparison Temporal evolution	Text
Engagement and performance	Radar chart	Individual and average class scores	Comparison	Text
Students' profiles	Scatter plot	None	Relationship between variables	Text
	Pie chart	Average class scores	Comparison	Text, color coding

this student has a global performance score equal to 37,87. We also provide students with an evolutionary

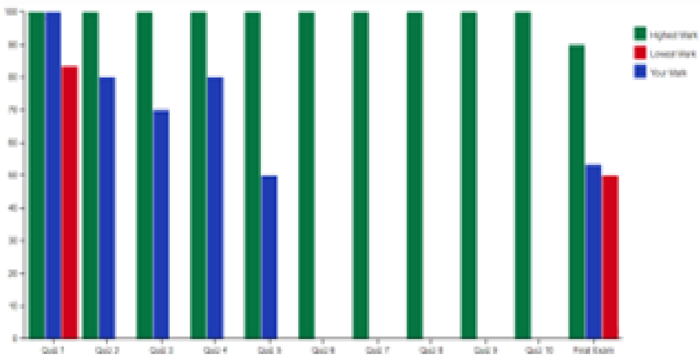


Figure 1: Evolution of the student 7's grades through the course

view of their engagement score for each quiz during the course. The bar chart presented in Figure 3 shows the engagement score of student number 7. By comparing this figure with the previous one, we understand the reason why this student got the lowest score of 0 for the quizzes from 6 to 10. In fact, he didn't even try to answer these quizzes which proves the relevance of the indicators we have proposed. Student 7 has an overall engagement score equal to 16.35. We can conclude from these scores that he/she does not log on regularly to the LMS, does not spend enough time there and does not interact sufficiently with the different activities. These results further explain the grades he/she obtained in the various quizzes which illustrates the relationship between our different indicators for analyzing the student's behavior and deducing the main reasons for the difficulties he is facing. The teacher also has a detailed view of his students'

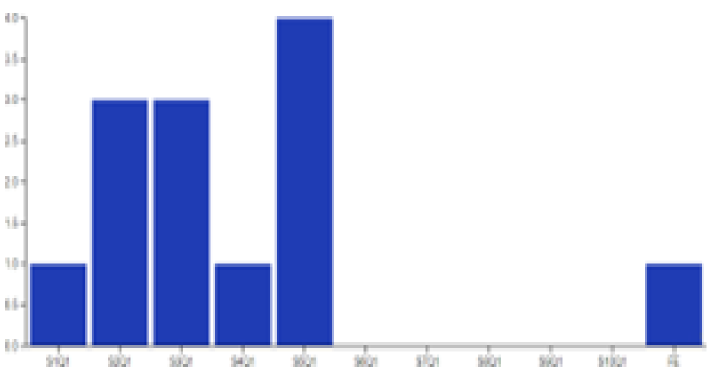


Figure 2: Evolution of the student 7's perseverance score through the course

performances, as shown in the bar charts in figure 4. These charts enable him/her to analyze in detail the evolution of students' grades throughout the course andto compare the obtained results. This visualization provides the teacher with valuable information for assessing student performance. The Bar chart presented in Figure 4 shows a comparison of students' scores and ranks in quiz number 5 which is an intermediate quiz .To view students' grades in a specific quiz, the teacher can select the desired quiz from the adjacent drop-down list (see figure 5). This feature allows the teacher to monitor student's progress and analyze the evolution of their results through the course as he/ she can detect the dropor the progress in the student's performance from one quiz to another. Then using a drill-down operation, the teacher is allowed to navigate from the whole class to visualize each student and compare his/ her values to the others as shown in figure 5. Figure 5 shows three stacked histograms where each bar represents an engagement indicator score: IOI, CACOI and CACOoI

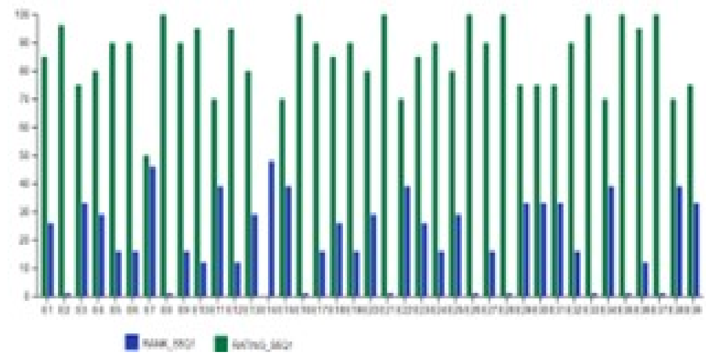


Figure 3: Comparison of students' grades and ranks for the Quiz n°5

respectively. To ensure the readability and clarity of the visualization, we chose to present only 15 students. The teacher may wish to have an overall view of the engagement of each student over the time spent on the platform, the number of connections and the number of clicks made online which reflects whether the student has done activities or consulted resources over the course. We have chosen to represent these three engagement indicators combined in a single figure to provide a comprehensive overview of student behavior on the e- learning platform. By visualizing these three indicators simultaneously, we can identify correlations between the number of interactions, the time spent on the platform and the frequency of connections. For example, an increase in time spent on the platform may be associ- ated with an increase in the number of interactions, as demonstrated in the case of student 11. On the other hand, opposite scenarios can also occur, as observed with students 6 and 14. Similarly, an increase in the number of connections does not necessarily guarantee that the student spends more time on the platform, as shown by the cases of students 4 and 13. Without the combination of these three indicators, we could have falsely concluded that these two students were among the most engaged, when this was not the case. In summary, this combined representation offers a deeper and more accurate understanding of students' behavior on the platform, enabling a better assessment of their actual engagement. In this figure, we have intentionally chosen not to include the perseverance indicator, be- cause as we have already discussed above, this indicator is more relevant to students with mediocre results and is closely associated with academic performance. By focusing on the three engagement indicators combined, we aim to provide a more holistic perspective on student behavior on the e-learning platform. We can see from

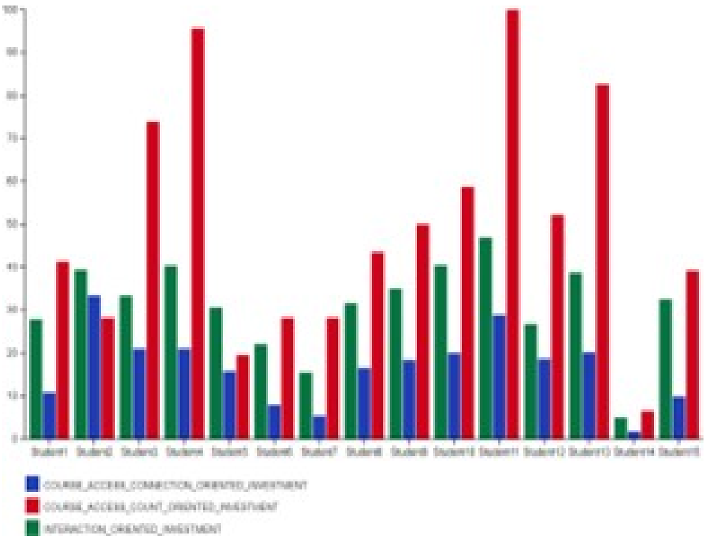


Figure 4: Overview of engagement indicators for the class

Figure 4 that Student 4 used the platform extensively as did Student 13. Both had a similar perseverancescore since they made 2 attempts on quiz 5. We can then conclude that these indicators are complementary to properly characterize student engagement. In this section we presented the various visualizations that allow us to display the indicators to our dashboard users. We demonstrated the effectiveness of these indicators and their relevance in allowing the teacher to clearly identify students with difficulties and easily conclude the type of difficulty they are experiencing, enabling him/her to intervene at the right moment and to adapt this intervention to the student's spe- cific needs. Students can also understand their own difficulties through these detailed indicators making it easier for them to overcome these problems. However, the ability of users to understand and interpret these graphs directly may vary. This leads us to our second research question in the next section.

RQ2: How can we create a dashboard that is understandable and interpretable by non-specialists in data analysis?

To address this research question, our study focuses onthe explainability of learning analytics through different graphs that are easy to understand and interpret by the different dashboard users .We demonstrated the importance of our proposed learning indicators in the previous section. This section is dedicated to the remaining criteria. First, we ensured our dashboard offered comparative views for both teachers (see figure 4) and students as shown in figure 5. Figure 5 offers a

global perspective of the various indicators calculated using the proposed formulas, through a radar graph. This radar graph highlights performance indicators, perseverance and engagement scores, comparing them with median scores. This

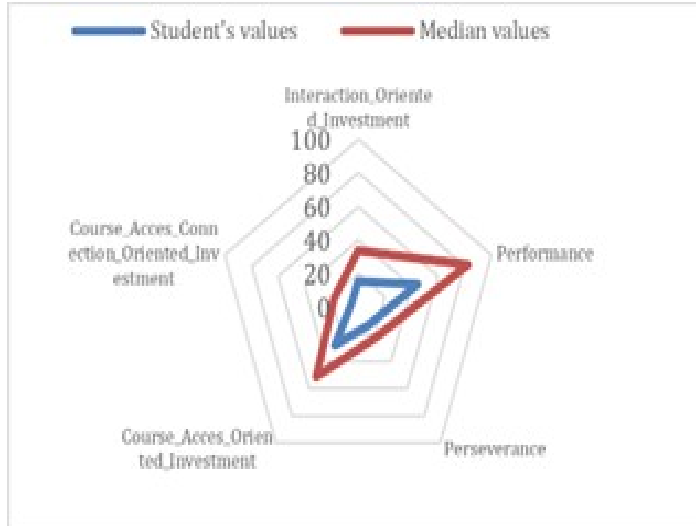


Figure 5: Global view of the student 7's engagement and performance indicators.

individualized view helps students situate themselves in relation to their peers and analyze efficiently their own academic problems. They can therefore understand their results which enables them to adopt the right measures to improve their academic performance. The bar chart in figure 8 demonstrates the relation- ship between the engagement and performance globalindicators for the whole class .This enables the teacher to confirm the results we have seen in the detailed views and thus take the right decision since he can understand that not only academic performance shouldbe used to evaluate the student as engagement may also influence these results. Another important criterion for

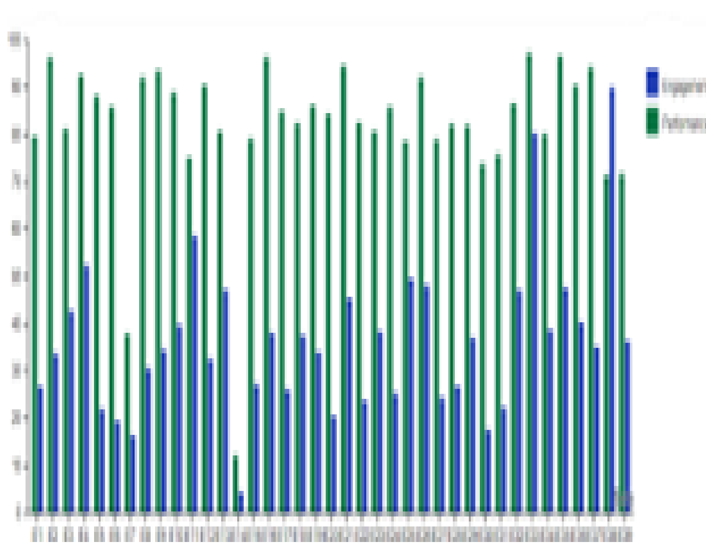


Figure 6: Overview of engagement and performance global indicators for the class.

achieving EX-LAD is to transform recommendations and predictions into actionable steps. In other words, it is not enough just to provide information, but also to facilitate decision-making and action based on this information. In fact, we also considered the feasibility of actions in our solution .We proposed different student profiles cal- culated according to their performance and engagement indicators. Instead of applying similar interventions to all students, we focused on tailoring actions to these profiles. These profiles may be detected with the scatterplots shown in figure 7. Figure 7 shows students' profiles' evolution through the course quizzes highlighting the relationship between performance and perseverance. This allows the teacher to identify specific students of a given profile and follow his/her individual evolution. Our goal is to help teachers to identify the students who share the same learning behavior and face the same difficulties to provide them with adequate assistance according to their specific needs. In addition, we

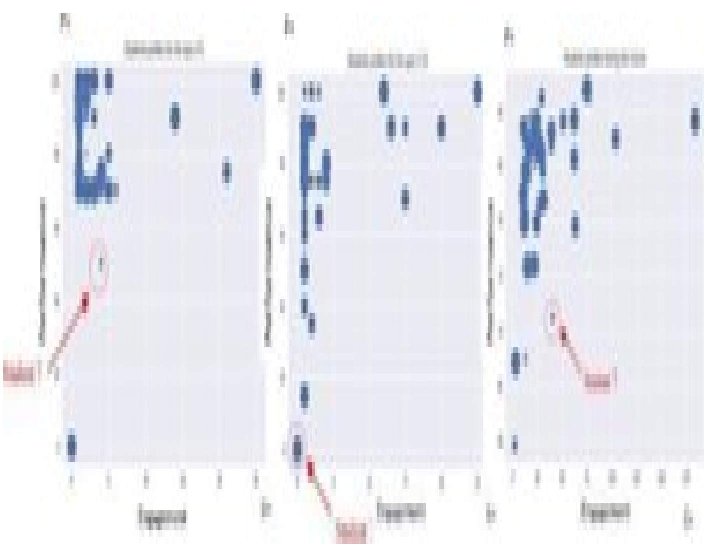


Figure 7: Students' profiles throughout the course quizzes.

also adopted the use of significant color coding in certain figures to emphasize the seriousness of the situation. This allows users to quickly grasp key information and identify important aspects of the data presented. The Bar charts in Figure 10 presents the evolution of this student's grades and perseverance score as well as his grades and his rank in each quiz. Student 7 had good grades for the first four quizzes however his results decreased for the following tests despite his efforts shown by his numerous attempts to respond correctly. We proposed a specific color code to highlight the significance of the presented values. Red was used to express seriousness of the situation and that an immediate intervention should be done after these dissatisfactory results. Green was used to express positive results. The choice of traffic lights' colors allows users to easily identify the indicators that need particular attention which facilitates the interpretation and decision-making. Our dashboard offers a variety of visualizations, each aimed at a specific objective, making it easier to interpret the displayed results. We have opted for bar charts or radars to provide a comparative view, scatter plots

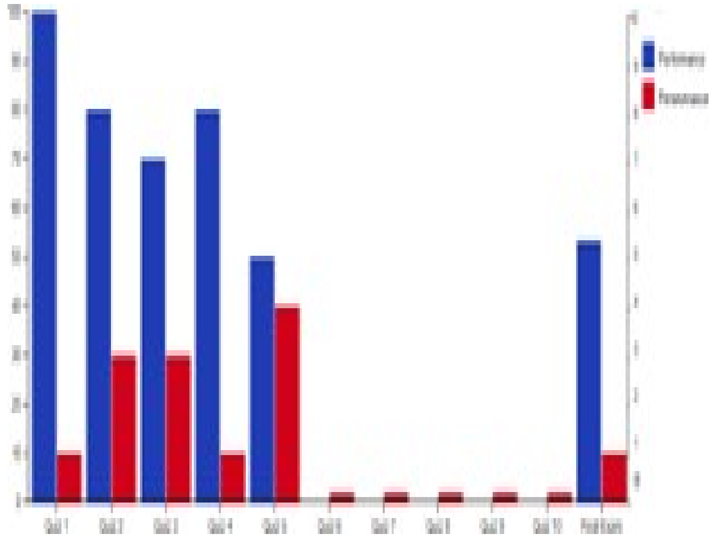


Figure 8: Student 7's grades and perseverance scores

to demonstrate relationships between variables as well as pie charts. Our dashboard offers a personalized approach that facilitates the identification of problems that are common for each group of students and allows the teachers to provide them with specific interventions tailored to their needs. This enables the students to improve their academic results and boosts their engagement and motivation.

5 Discussion

We have successfully developed a student-centered dashboard aimed at empowering students to self-assess and enhance their learning journey, while equipping teachers with the necessary tools to monitor progress and identify those at risk of academic setbacks, enabling timely intervention. Ensuring the dashboard's accessibility to all stakeholders was a key priority to maximize its effectiveness. However, we encountered several challenges along the way. Understanding the database structure of the Learning Management System (LMS), particularly Blackboard Learn, proved to be a significant hurdle. Efficiently accessing and extracting data and metadata necessitated an in-depth examination of the system and data management practices. Moreover, the dashboard has certain limitations associated with the available raw data. For instance, some indicators cannot be recalculated over time, hindering the representation of longitudinal trends. For example, data on clicks and LMS accesses were only available for the entire course duration, rather than at different time intervals. Furthermore, we faced challenges related to compliance with GDPR regulations .Securing consent from all students can be challenging, resulting in a limited dataset and potentially compromising result quality. In cases where certain student profiles are under- or over- represented in the data, biases may be introduced. It is crucial to consider these challenges when implementing data-driven techniques.

6 Conclusion and Future works

A crucial aspect of our proposed dashboard is to ensure that the proposed visualizations are comprehen- sible to all users, as part of the Explainable Learning Analytics (EX-LA) .This means that the presented informations are clear and easy to interpret, enabling every user, whether student or teacher, to quickly draw relevant conclusions from data analysis. By integrating explicit and intuitive visualizations, we strive to ensure that our dashboard is truly informative and useful for all players involved in the learning process. We attach great importance to trust and transparency in the use of data .Therefore, our dashboard offers a textual explanation of the indicators calculated and used in the visualizations. User-friendliness of the dashboard is an essential consideration. Ethics is a fundamental aspect of our solution .Although we provide students with comparative visualizations to encourage them to situate themselves in relation totheir peers, we took care not to mention the name of any student when displaying best and worst grades. In this way, we respect the confidentiality and protection of students' personal data. We integrated as well, a chat section enabling students to decide whether they wish to communicate directly with their teachers and receive personalized interventions. Our solution aims to maximizing the success of all students, not just those experiencing difficulties. This is demonstrated by the assistance offered to students with the E+P+ profile who have no difficulties. We value equal opportunities and promote success for all. In this article, we analyze the evolution of student performance over time. However, due to the insufficient temporal granularity of the raw data, we are unable to conduct an in-depth study of the evolution of student engagement. In our ongoing research, we aim to utilize richer data with a finer temporal granularity to align with the objectives of studying indicator evolution. Our objective is to enhance our ability to detect student difficulties early .While this article presents representations of indicators based on measured data, our future direction involves leveraging these datato predict the evolution of student difficulties using machine learning techniques .We are committed to maintaining transparency in these predictions, ensur- ing that the criteria used for predictions are clearly communicated to end-users, whether they are studentsor teachers. This approach fosters understanding and confidence in the predictive processes. The outlined requirements and concerns underscore the importance of having a large dataset with a substantial number of observations, allowing for the calculation of numerous indicators over time .Given the complexity of this task, exploring alternative solutions such as leveraging existing datasets is under consideration. However, comprehensive comparisons of available datasets, including their characteristics and ethical assurances, are lacking. Therefore, a detailed assessment of available datasets remains a major focus of our ongoing work.

7 Acknowledgements

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