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EX-LAD: an Explainable Learning Analytics Dashboard in Higher Education

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Abstract

This paper introduces an **EX**plainable **L**earning **A**nalytic **D**ashboard (EX-LAD) that presents learning analytics data on student performance, engagement, and perseverance in a clear and easily understandable manner. The main goal of this study is to make this information accessible to both teachers and students, who may not possess extensive knowledge in data analysis, and demonstrate the effectiveness of the relationship between performance, engagement, and perseverance in identifying student difficulties. This dashboard enables teachers to gain valuable information about their student's progress, identify at-risk learners, and provide targeted support. Similarly, students can use this dashboard to track their own learning journey, identify their strengths and weaknesses, and make informed decisions to improve their academic performance. It integrates visualizations to represent various aspects of student learning, such as performance, engagement, and perseverance. To demonstrate the effectiveness of our dashboard, we conducted a case study using real data collected from ESIEE-IT, an engineering school in France, during the academic year 2021-2022. This case study serves as concrete evidence of the impact and values our dashboard brings to the educational context.

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 leveraging Learning Management Systems (LMS). LMS's 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 universities, and BlackBoard Learn [2], which is of interest in our study. Although these platforms provide learning analytic dashboards to showcase valuable information, they often face two significant challenges. Firstly, they tend to prioritize student performance solely based on their achievements and academic results [3, 4], such as grades obtained in various activities. Unfortunately, this narrow focus often leads to overlooking other crucial indicators, including engagement (cognitive, behavioral, social, etc.). As a result, there is a pressing need for a more comprehensive 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 analysis. Dashboards with complex 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 commu^{2}nicating the data. However, they are often considered difficult to understand and interpret [5]. To address this thinking, a new field called "Explainable Learning Analytics" has been introduced. Therefore, our research questions are the following:

- **RQ1**. What are the necessary indicators to support students and teachers when using LMS?
- **RQ2.** How can we have a learning analytic dashboard that is understandable and interpretable by non-specialists in data analysis?

To address these research questions, we developed an EXplainable Learning Analytic Dashboard (EX-LAD) that presents learning analytics data on student 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 own 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 paper is organized as follows: Section 2 presents some recent learning analytics dashboards conducted 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 presents our future works.

2 Related works

In this paper, we focus on the usefulness of learning analytics dashboards for monitoring students and detecting 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) communities. We conducted keywords-based queries such as 'learning analytic', '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 found over 670 research articles. We read their abstracts and selected those that presented empirical research on Learning Analytics, which offered relevant empirical research conducted in higher education all over the world. We excluded review articles and theoretical articles that focus on the LAD aspects. Following this methodology, we finally selected 8 papers that we analyzed in depth. Table 1 summarizes the selected studies according to five main criteria which are: (a) target users, (b) data protection, (c) learning indicators, (d) visualization and (e) insightful actions:

(a) Target users (TU) represent the final users of the dashboard who can be students (S) and/or teachers (T).

(b) Data protection (DP) indicates whether the researchers proceeded to data anonymization to guarantee the ethical use of data by teachers and the educational team.

(c) Learning indicators represent the specific type of indicators used in the dashboard that may include performance indicators (P), cognitive engagement indicators (CE), behavioral engagement indicators (BE), social engagement indicators (SE), and more.

(d) Visualization is defined based on three main criteria which are: (i) Number of visualizations and chosen techniques, (ii) explainability and (iii) objective of visualization.

- *Number of visualizations and type*. This criterion focuses on the variety of the visualizations proposed in the dashboard (for example scatter 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 recommendations or notifications.

Ref.	**TU**	**DP**	**Learning Indicators**				**Visualizations**			**Actions**
			P	BE	SE	CE	Number and type	Explai-nability	Objective	
[7]	S	✓	✓	✓	✓	✓	5 Bar charts, 1 Linear Graph, 5 Line charts, 1 Gauges, 1 Tree graph	*	Comparison, Evolution,	*

[8]	S	✓	✓	*	*	✓	5 Line charts, 1 histogram	Text	Evolution	*
[9]	S/T	✓	✓	✓	✓	✓	6 Tables,3 Line charts, 1 Bar chart, 1 Pie chart	*	Comparison, Evolution,	Notifications
[10]	S	✓	✓	✓	✓	*	2 Bar charts,1 Gauge, 1 Line chart, 2 Column charts	*	Comparison	Recommendations
[11]	S/T	✓	*	*	✓	*	1 Radar chart, 1 Network Graph, 1 Bar chart	Text Color Coding	Data distribution	*
[12]	T	✓	✓	✓	*	*	2 Bar charts,3 Tables	Color Coding	Data distribution	*
[13]	S	✓	✓	*	*	✓	1 Pie chart, 1 List, 1 Table	*	Data distribution	*
[14]	S	✓	✓	*	*	*	1 Radar chart, 1 List, 1 Scatter Plot	*	Data distribution, Evolution	Recommendations

Target Users (TU), Data Protection (DP), Students (S), Teachers (T), (✓)Yes, (*) No

Table 1: Comparative table between existing learning analytics dashboards.

Based on the works we studied, we made some observations. First, we observe that most of the studies [7]–[10], [12]–[14] used the performance indicator, which is derived from student grades (see [15]). We also note a diversity in the proposed engagement indicators. For example, works [7], [8], [9] and [13] focus on cognitive engagement, while learning analytics dashboards [7], [9], [10] and [12] deal with behavioral engagement, and [7], [9], [10] and [11] address social engagement. Most of these works were limited to two indicators, namely performance and an engagement indicator, except for [7] and [9], which combined all four indicators. However, most studies opted for a straightforward presentation of data in the form of visualizations, without developing the formulas for calculating indicators or clearly identifying engagement and performance. One exception is [9], which has developed several scores to facilitate the understanding of each indicator. Nevertheless, although several different learning indicators were proposed, visualization options remain limited. Most studies relied mainly on bar charts, curves, or even tables and lists. A few exceptions, however, introduced scatter and radar plots, as referenced in articles [14] and [11]. It is observed that the works presented did not pay particular attention to the comprehensibility or explicability of their visualizations. Given the limited choice of visualizations available, there is a risk that users will find it difficult to understand the presented results. However, a few exceptions were noted, notably in works [8] and [11], where text descriptions were provided, and sometimes significant color choices were used, such as traffic light colors in works [11] and [12]. Another observation is that the presented learning analytics 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. Finally, it is important to note that only three studies provided their users with insightful actions. [14] et [10] delivered personalized recommendations to the students using their dashboards and [9]'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 objectives, we placed 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. In the next section, we describe our proposed 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 Participants

We conducted a case study with real data collected from the LMS used by an IT school called ESIEE-IT[16]. 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.

3.2 Study context

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. Indeed, 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 attachment or directly in the document, and (d) the quizzes composed of 5 to 10 questions delivered as assessment activities and a final test made of 20 questions. Student interactions with BlackBoard Learn [2] were recorded in the Snowflake data warehouse. These interactions include data such as number of clicks, time spent on the platform, 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.

3.3 Steps of the proposed EX-LAD

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

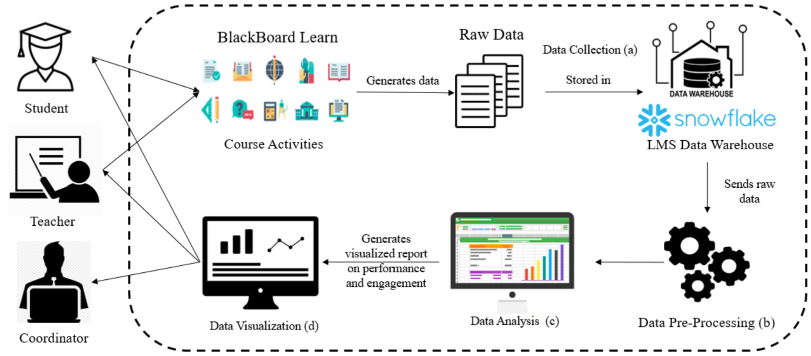

Figure 1: The dashboard development steps.

- ## 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 students'. Table 1 describes these different features. It is made up of different parts describing the various features of our dataset. The first part includes the student's personal data which is name (1), e-mail address (2) and course of study (4). The second part is related to the student's access to the platform, such as 'Course_Access_Connection' and 'Course_Access_Minutes'. The following part concerns academic performance, including grades, ranks, number of submissions and average score. Engagement indicators are described in the next section: 'Interaction_Oriented_Investment (IOI)', 'Course_Access_Connection_Oriented_Investment (CACOoI)' and 'Course_Access_Count_Oriented_Investment (CACoI)' . Finally, the last feature 'Difficulty' contains four values representing the different profiles of students according to the problems they encounter which are as follows: 'E+P+', 'E+P-', 'E-P+' and 'E-P-'.

	Feature Name	T	Feature Meaning	Value Example
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
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
9	T_Exe_Submission_Count	I	Total number of attempts in quizzes	10
10	Rating_SiQ1	F	Score of quiz n° 1 in the sequence number 1	80
11	Rank_SiQ1	I	Rank of the student in the quiz n°1 in the sequence number 1	6
12	SiQ1_Exe_Submission_Count	I	Number of attempts in the executable activity Quiz number 1 of the sequence number I	2
13	Diff_Rating_SjQ1	F	The difference of score between the actual quiz in the actual sequence and the last one	20
14	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
15	Rating_Final_Exam	F	Score of the final exam	75
16	Rank_Final_Exam	I	Rank of the student in the final exam	3
17	FE_Exe_Submission_Count	I	Number of attempts in the final exam	1
18	Diff_Rating_Final_Exam	F	The difference of score between the final exam and the last executable activity	-20

19	Diff_Ranking_Final_Exam	I	The difference of rank of the student between the final exam and the last executable activity	23
20	Avg_Rating	F	The average score in all executable activities	38,75
21	Rank	I	The rank of the student in the class	20
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	32,9588
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	23,6666
25	Engagement	F	The average of the four investment scores to measure the engagement of the student	66,84367
26	Difficulty	O	Type of difficulties of each student depending on the calculated scores.	E+P+, E+P-, E-P+ E-P-

T: type, O: object, I: integer, F: float, T: timestamp, i={1..10}and j={1..10}

Table 2: Dataset Features.

All these indicators are described according to equations presented below:
Performance. is calculated through the grades of the student in the executable activities using his/her grades in the quizzes (Q) (50%) and the final exam (50%) using the following score:

$$\text{Performance} = \mathbf{0.5} * \boldsymbol{Average}(\boldsymbol{Q1}, \boldsymbol{Q2}, \ldots \ldots, \boldsymbol{Q3}) + \mathbf{0.5} * \boldsymbol{FinalExam} \tag{1}$$

A student is considered successful if his or her average exceeds 50 and failing if it does not. we must mention 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.).
Engagement: is defined as ‘the active involvement of learners in a learning activity and any interaction with teachers, other learners or learning content through the use of digital technology’ [17]. To calculate it, we compute four different scores.

- Interaction oriented investment (IOI) is calculated as follows:

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

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).

- Course Access Connection Oriented Investment (CACOoI) calculated as follows:

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

- Course Access Count Oriented Investment (CACoI) defined as follows:

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

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

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 values over time. On the other hand, we could collect 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 its evolution during the course.

- **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 the 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.

- **Step3. Data visualization**

We proposed in our dashboard a set of visualizations that meet certain criteria and offer a set of features as shown in the table 3. This table explains how we presented the indicators that we calculated. We used various forms 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.

LA indicators / Data	Visual Charts	Comparative data	Objective	Explainability
Student's ranks	Bar chart	Individual and class scores	Comparison	None
Student's grades	Bar chart		Temporal evolution	Color coding
Ranks and grades	Bar chart			None
	Bar chart combined with line chart	Individual values and class median	Comparison Temporal evolution	None
Perseverance score	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 and Color Coding

Table 3: The EX-LAD visualizations and their characteristics.

In the following section, we present the actions to be taken from this dashboard.

- **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 perseverance 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 perseverance 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 perseverance. This student is really dedicated to his studies, but he/she fails despite his/her efforts, therefore needs an 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 performance 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 dashboard interfaces.

4 Experimentations results

- **RQ1: What are the necessary indicators to support students and teachers when using LMS?**

To answer our first research question, we present the learning indicators proposed in our dashboard for both students and teachers.

To assess student performance, we developed 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 this student has a global performance score equal to 37,87.

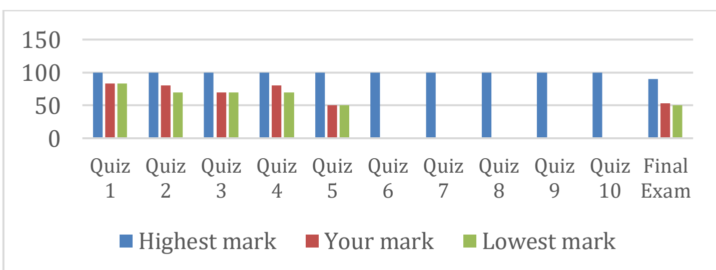

Figure 2: Evolution of the student 7 grades through the course

We also provide students with an evolutionary view of their perseverance score for each quiz during the course. The bar chart presented in Figure 3 shows the perseverance 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.

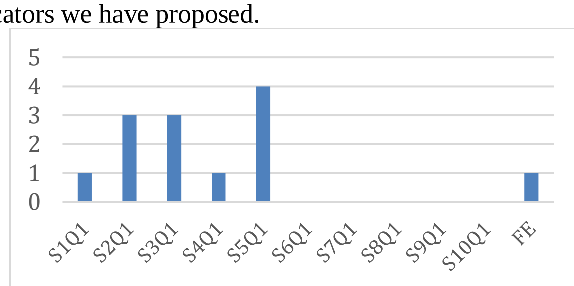

Figure 3: Evolution of the student 7 perseverance score through the course.

Student 7 has an overall engagement score equal to 16.35. We can conclude from these scores that he/she doesn't log on regularly to the LMS, doesn't spend enough time there and doesn't interact sufficiently with the different activities. These results further confirm 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' performance, as shown in the bar charts in figure 4. These charts enable him to analyze in detail the evolution of students' grades throughout the course and to 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.

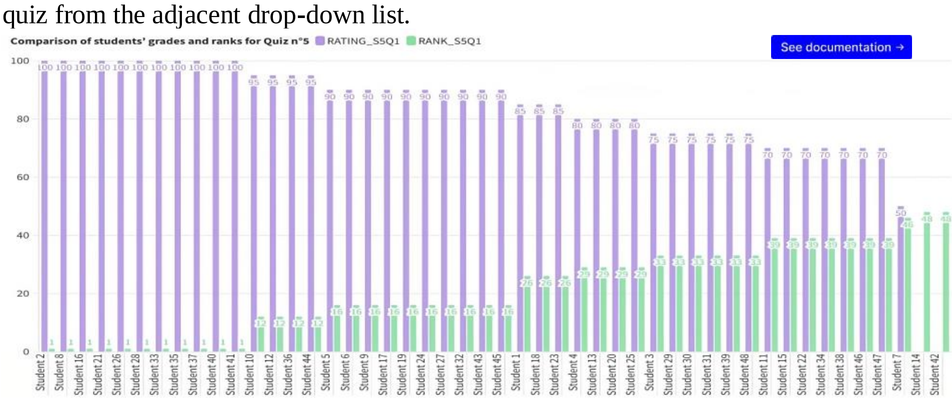

Figure 4: Comparison of students' grades and ranks for the Quiz n°5.

This feature allows the teacher to monitor student's progress and analyze the evolution of their results through the course as he/ she cand detect the drop or 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 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 through 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.

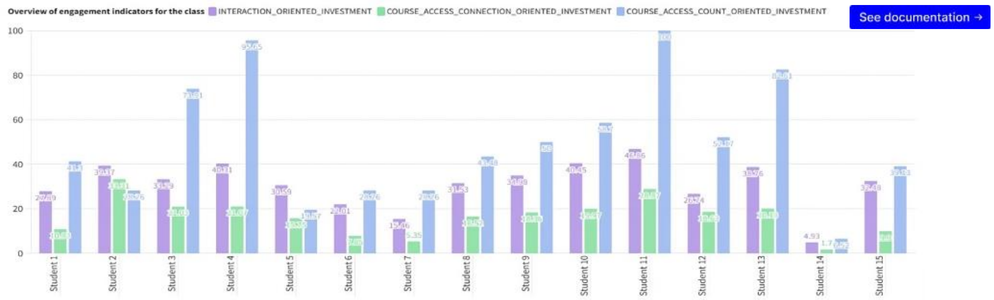

Figure 5: Overview of engagement indicators for the class

We can see from Figure 7 that Student 4 used the platform extensively as did Student 13. Both had a similar perseverance score 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 specific 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 have a dashboard that is understandable and interpretable by non-specialists in data analysis?**

To address this research question, our study focuses on the 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 5) and students as shown in figure 6.

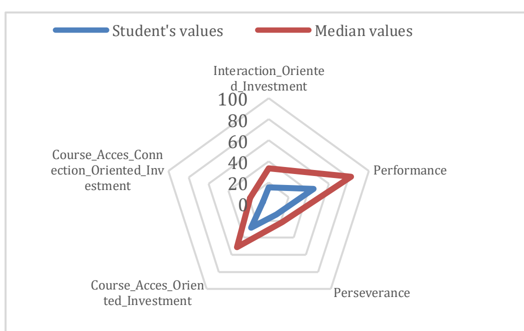

Figure 6: Global view of the student 7 engagement and performance indicators.

Figure 6 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 individualized view helps the students situate themselves in relation to their peers and analyze efficiently his/her 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 7 demonstrates the relationship between the engagement and performance global indicators for the whole class which 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 should be used to evaluate the student, but also engagement can influence these results.

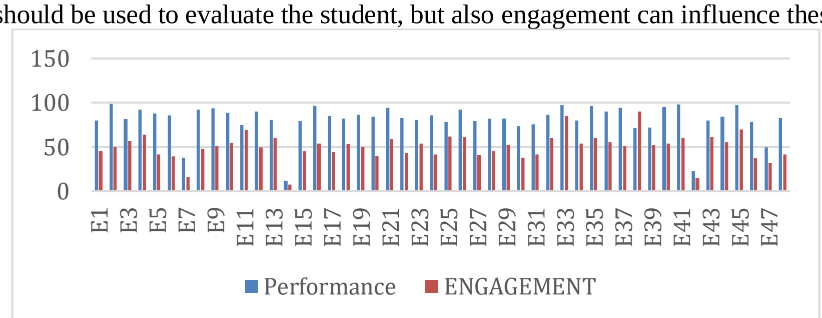

Figure 7: Overview of engagement and performance global indicators for the class.

Another important criterion for achieving EX-LAD is to transform recommendations and predictions into actionable steps. In other words, it's 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 calculated 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 8. Figure 8 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.

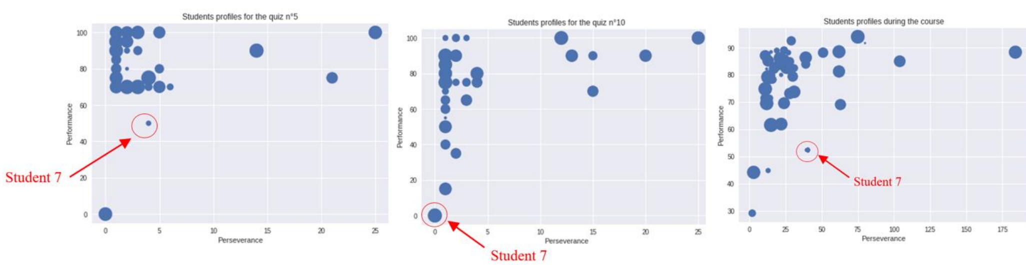

Figure 8: Students' profiles throughout the course quizzes.

In addition, we 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 9 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.

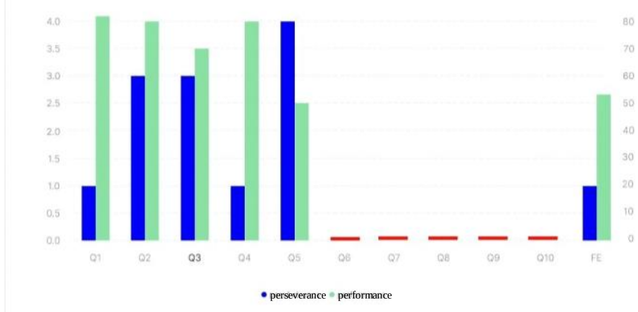

Figure 9: Student 7's grades and perseverance scores.

Our dashboard offered 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 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 Conclusion

A crucial aspect of our proposed dashboard is to ensure that the proposed visualizations are easy to understand. 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 to their 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. As perspectives for this work, we propose in the first place to enrich our learning indicators by including emotional and social engagement alongside with the behavioral engagement and we suggest detailing the performance indicators as we have already dealt with the performance in general. These additional dimensions offer a complete comprehension of the student's learning process.

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