Design of a learning progress visualization tool and its impact on students' motivation and results: a case study

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***Abstract*—Self-awareness of achieved learning progress is crucial for students to identify strengths and areas needing improvement, as well as to boost their motivation. Learning Analytics approaches are one way to provide such information about learning progress. In this paper, we describe the design of a visualization tool that enabled students to track their progress in the topics covered throughout a university course. We also investigate its impact on students' results and motivation to participate in optional learning activities. This learning analytics tool was integrated into the corresponding Moodle page for an entire semester, and it monitors different results of the students in the activities of the course to estimate their achieved progress. Optional review activities of the topics covered in the course were available for all students, with the intention that increasing learning progress awareness also fostered participation in such activities. To evaluate the impact of the visualization tool, we analyzed and compared the behavior of two groups of approximately 20 students, with and without access to the tool during the whole semester. Our findings indicate that when they had access to the progress visualization, students completed more review activities overall in all course topics and were more consistent in their review activities throughout the course, while those in the control group engaged with these activities primarily near course deadlines. These promising results will be further investigated with larger datasets in future courses. The design of the visualization and the methodology employed in this study could be adapted to other courses to further expand and generalize our results.**

***Index Terms*—Learning Analytics, progress visualization, dashboards, learning awareness, self-regulated learning, student motivation, Moodle.**

I. Introduction

Learning Analytics (LA) aims to gather and analyze student data to better understand and improve the learning process [1]. The application of LA in educational contexts has grown substantially in recent years, mainly promoted by the increased use of Learning Management Systems (LMSs) in educational institutions, and the expansion of Massive Open Online Courses (MOOCs), both of which provide large amounts of LA data [2]. Such interaction data can be analyzed for multiple purposes, including the prediction of student success rates and dropout in MOOCs [3], or the early detection of students at risk of failing the course [4] commonly applied in LMSs, combined with recommendations to take the corresponding actions to prevent such failure.

With the analyzed data, a common further step is to design and develop LA dashboards [5] or visualizations to provide students, or other interested stakeholders, with the information gathered in an easy-to-understand visual way. With the received information, students should be better informed of their actions and learning progress, ultimately increasing their awareness about their learning progress, and being also better prepared to make decisions to improve it.

The information gathered from LA systems could contribute to self-regulated learning strategies and foster motivation. As one of the different factors that impact students' learning process, motivation is commonly studied and addressed by educators and researchers [6], [7]. Motivation may be fostered through several ways, including increasing student awareness about their progress and results. In particular, to improve students' efficacy for learning, research has pointed out several strategies including breaking down difficult learning goals into smaller subgoals and providing students with information about their progress [8].

In the learning technologies research area, multiple approaches are developed to increase the motivation and interest of learners [9]. Some examples are Game-Based Learning techniques [10], which apply computer games to attract students to learn new concepts or skills, Augmented Reality [11] to display virtual objects in real environments, and Mobile Learning [12], where students use their tablets and smartphones to consume course content. Another common strategy is the use of LA, which could be combined with other learning technologies.

This paper presents a case study that describes the design of a visualization of students' learning progress in a university course and measures its impact on students' participation in optional learning activities. The visualization displays achieved progress in each topic within a course, based on a series of activities and tasks performed by students in the course and related to each topic. The impact of the visualization was mainly measured in this study as students' participation in review activities provided for each topic, which were optional and did not contribute to the final course marks.

The main research objectives of this study are:

1) To measure the impact of visualizing learning progress in completing optional activities.
2) To measure the consistency of participation when the visualization of progress is available.

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This study was conducted on two groups of university students. The first (experimental) group had access to the visualization tool, while the other (control group) did not. The results demonstrate an increase in student participation when they have access to visual representations of their progress. This underscores the potential usefulness of such tools in boosting student motivation.

The rest of the paper is organized as follows. First, Section II analyzes relevant works in the field of motivation and the use of LA to improve students' motivation and participation, particularly the use of Visual Learning Analytics. Section III describes the methodology applied to the study, including the research questions that guided the study, the design of the visualization of progress, participants, and data analyzed. Next, Section IV details the results obtained from both groups of students, and discusses each research question accordingly. Finally, we present the main conclusions of this study and discuss its limitations and some future lines of work in Section V.

II. Related Work

A. Importance of Awareness and Motivation for Learning

While multiple factors can impact students' learning strategies and results, for self-regulated learning (SLR) strategies, motivation is one of the keys to students' success [13]. To keep students motivated, several factors come into play, including, but not limited to: the sense of control, competence perceived, having a way to self-evaluation, and setting up specific goals [14], [15]. Motivation could be increased by social comparison with similar peers [16] and by having a goal-oriented approach to learning [17]. For instance, Schunk [18] found that providing progress feedback, along with specific goals, had the greatest impact on self-efficacy and achievement. This aligns with the *self-efficacy theory* [19], which states that the perceptions that learners have about their abilities and competencies are essential for them to complete their learning goals. This theory details that learning is achieved from multiple factors, including students' perceptions of their past performance, and the feedback received [20]. The most adequate feedback to give to students provides information about progress [21], increasing students' awareness about their learning so far, as well as indications on how to continue improving the learning process. Additionally, this tends to align with the general preference of the students. A natural way to provide that feedback is goal-directed [22], that is, providing information on students' progress towards a specific desired goal as a result of their goal-driven activities.

B. Approaches to Increase Motivation in Learning Contexts

While providing feedback can be a factor, it is not the only way to increase student motivation in learning scenarios. In fact, the factors for motivation in education have long been studied and changed over the decades [23]. Current approaches to increase students' participation and motivation in the classroom include the use of gamification [24] in learning contexts, i.e., the integration of elements typical of games in other contexts or activities. For instance, using badges or leaderboards to provide information about learning achievements and comparison with peers. Specific tools to introduce quizzes of playful activities in classrooms, such as Kahoot![1], are being integrated into classroom scenarios to engage students and motivate them in different learning activities. Data analysis techniques can also be applied to the large amount of interaction data generated in learning scenarios for several goals, including a better understanding of the learning process or providing specific information for students that could increase their participation or motivation. These techniques for educational data correspond to the field of Learning Analytics.

C. Learning Analytics

The expansion of data analysis has also reached the educational field. LA is the discipline that aims to gather and analyze data about students in learning contexts to better understand their learning process and improve it. The information gathered from LA data can be used for a multitude of purposes and stakeholders: providing real-time feedback to students and teachers, creating learners' profiles so teachers can better understand and adapt the classes to each student's needs, assessing their learning results, etc. [25]. Institutions can also benefit from the use of LA techniques, as they can gather information about their students' learning process and results, to better understand it and improve the curriculum.

The new technologies and learning environments have increased the amount of LA data gathered from students and the opportunities to provide feedback on their learning progress and increase their motivation [26]. That is the case of MOOCs and LMSs, which make it possible to gather more interaction data as well as to provide information for students and motivate their learning process [27]. MOOCs can easily integrate LA features since their learning scenario is completely online, thus intrinsically having all student interactions in their platforms. This allows the provision of tailored feedback to adapt the learning process of each student individually while gathering overall data to extract general conclusions. Meanwhile, LMSs are the standard platform used in universities to share materials, hand in homework, and even assess students. Even if the learning scenario is still in-person, many interactions related to that learning process and evaluation are carried out within the LMS, consequently providing many opportunities to gather LA data. Some of these systems have already incorporated LA features; such is the case of Moodle, which includes Analytics features[2], or the Open edX platform, which incorporates analytics such as near real-time dashboards[3].

D. Visual Learning Analytics and Motivation

To facilitate the understanding of LA information by different stakeholders, LA dashboards or visualizations are commonly used in learning scenarios [28], [29]. In fact, most

[1] https://kahoot.com/

[2] https://docs.moodle.org/dev/Analytics_API.

[3] https://openedx.org/.

LA studies conducted in recent years included some form of data visualization techniques, using diverse sources of information for their dashboard designs and translating those varied and large datasets into visually interpretable formats for stakeholders [30].

Regarding the recent field of learning analytics dashboards, most studies are exploratory or proof-of-concept, mainly being conducted by providing dashboards for teachers or students in formal learning scenarios and university settings [31]. In particular, learning dashboards mostly provide information for individuals or the whole class for self-monitoring purposes, with Moodle being the most popular platform for gathering data. To address the issues encountered in previous research, it is essential to adopt proper visualization techniques as users may be overwhelmed or confused by the information presented [31]. Artificial Intelligence techniques are also included in some cases to predict students' results and recommend interventions for teachers [32].

In these experiences, learning analytics dashboards were also found to increase students' motivation, compared to those without access to them, resulting in higher scores throughout the course and in the final grades [33]. Some studies have also explored the relation between learning analytics dashboards and motivation, finding promising results as some students may feel more motivated when compared to their more advanced peers [34].

E. Current proposal

Following these previous works, we designed and developed an LA visualization system to increase students' awareness about their progress and tested it in the context of a university course, as the visualization tool was integrated into the Moodle LMS. To further analyze how the visualization motivates students to improve their progress, we complemented it with additional review activities, which were optional and available to all students. Our initial expectations, aligning with previous literature, were that the visualization would increase learners' awareness and motivation to complete such optional review activities. To test this, we gathered data from two groups of students, only one of them with access to the visualization tool. The methodology, results, and conclusions of this study are explored in detail in the following sections.

III. METHODOLOGY

The main goal of our study is to analyze the impact of the progress visualization system on students' participation and results in a university course. To that end, we compare the behaviors of two groups of students taking the same course. The first group (experimental group) had access to the visualization tool on their Moodle website. This tool showed each student their progress in the course topics. The other group (control group) did not have access to such visualization. Optional review activities about all course topics were included and available for both groups.

We describe next the research questions initially posed, and the methodology of the study, including the design of the progress visualization, the materials used, and the data extracted from the Moodle platform to analyze the results of the study.

A. Research Questions

In the study analysis, we delineated two groups of research questions. The first group focused on the students' interactions with the visualization tool. Our interest lies in observing the use and efficacy of the tool for the students. To address this, we formulated the following research questions:

RQ1 Do students in the experimental group access the visualization tool consistently throughout the course?

RQ2 Do students in the experimental group engage in optional review activities after accessing the visualization tool?

The second set of research questions aimed to compare participation and grades between the two groups of students. For this purpose, we formulated the following research questions:

RQ3 Do students in the experimental group complete more optional review activities compared to students in the control group?

RQ4 Do students in the experimental group engage in optional review activities more evenly throughout the semester compared to students in the control group?

RQ5 Do students in the experimental group attain higher average scores in the optional review activities compared to students in the control group?

RQ6 Do students in the experimental group achieve higher final scores in the course than students in the control group?

B. Materials

As stated above, in this work we included two new resources in the Moodle course webpage: the visualization progress tool and a set of review activities for each course topic. We describe each resource and its role in the study in the following.

1) Progress visualization: The visualization progress tool is the primary resource that we aimed to evaluate in this study. It provides information on the progress in each of the seven main topics of an Operating System course: (T1) introduction to shell and threads; (T2) processes and program execution; (T3) files and pipes; (T4) signals; (T5) semaphores; (T6) shared memory; and (T7) message queues. Figure 1 shows how a student engaged with the visualization tool during the study. This tool displays two types of progress for each learner: the individual progress for each topic, represented by the set of progress bars on the left, and the average progress of the entire group, represented by the set of progress bars on the right.

During the design process, the initial step was to enumerate a set of activities to incorporate into the progress evaluation. In particular, the value of each course topic was calculated based on relevant actions that students complete during the course and other metrics that can be tracked, such as the grade obtained in each activity. Bearing this in mind, we considered the following items to evaluate the student progress: grades

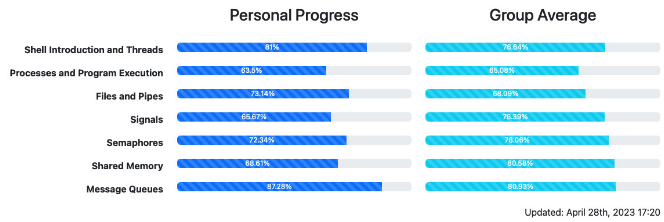

Fig. 1. Visualization tool, integrated within the course Moodle webpage, showing personal progress (left) and average progress of the group (right) in each of the 7 course topics.

from optional review activities, grades obtained in the practical delivery, grades from a short exam covering the practical topic, and attendance to the theoretical class where the topic is explained. We considered that, with these four actions, a student could reach full progress in a course topic. Additionally, some students attend individual tutorials to reinforce concepts taught in class or to clarify doubts. We found it pertinent to include this activity in the progress evaluation, even though not all students participated.

The subsequent step was to determine the weight assigned to each action in the progress evaluation. The primary goal of this tool is to motivate students to continue engaging in activities. Therefore, we assigned a greater weight to activities that can be repeated within the progress system. This approach allows students to receive more immediate feedback than relying solely on final marks, such as those from the practical topics. With these considerations, the student's progress value in a topic x, namely V_x, was calculated using the following equation:

$$\begin{aligned}\mathrm{V}_x = \min(100, 0.4\mathrm{RA}_x + 0.3\mathrm{PD}_x + 0.2\mathrm{PE}_x \\ + 0.1\mathrm{A}_x + 0.1\mathrm{T}_x).\end{aligned} \quad (1)$$

This equation incorporates the following metrics for the topic x: the grade calculated from review activities (RA_x), the grade obtained in the practical delivery (PD_x), the grade from a short exam related to the practical topic (PE_x), an indicator of the attendance to the theoretical class (A_x), and, finally, the attendance to individual requested tutorials to clarify concepts of the topic (T_x). As tutorials were optional, a $100\,\%$ score can be reached without them; therefore, the formula restricts the maximum value, including tutorials, to $100\,\%$.

Concerning the student's progress in the review activities, RA_x, it was not straightforward how to measure this component since, as we will detail next, there is no limit to the number of attempts that students can undertake. Furthermore, we aimed to assign greater weight to the results of the most recent trials so that students receive feedback based on their most current understanding of the topic. To consider this, it was decided that RA_x is calculated using the grades of the last three attempts of the review activities through the following equation:

$$\mathrm{RA}_x = 0.6\mathrm{RA}_x^{(t)} + 0.3\mathrm{RA}_x^{(t-1)} + 0.1\mathrm{RA}_x^{(t-2)}.$$

This approach assigns the highest weight to the most recent attempt made by the student ($\mathrm{RA}_x^{(t)}$), then a smaller weight

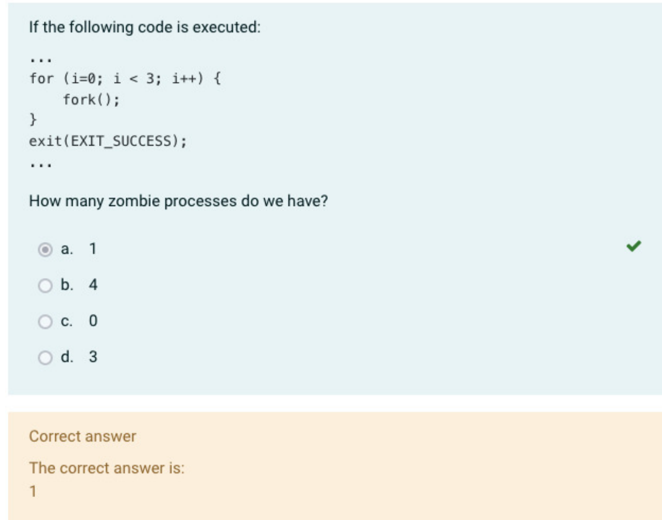

Fig. 2. Example of an optional review activity and the corresponding feedback showing the correct answer.

to the previous attempt ($\mathrm{RA}_x^{(t-1)}$), and finally the antepenultimate attempt ($\mathrm{RA}_x^{(t-2)}$) had the smallest impact.

2) Review activities: Another component included in the course was the review activities. These activities were created as a review mechanism so students could self-evaluate their understanding of each course topic whenever they wanted to, and test how much they knew about a given course topic. Additionally, they provide the possibility to compare participation in these optional review activities between the two groups of students.

For each course topic, we designed a question bank that included multiple-choice questions related to concepts explained in class. Each question presented four possible answers, with one being the correct answer (see Fig. 2 for an example). Within the Moodle course, each topic featured a quiz containing three randomly selected questions from the respective question bank. Students could engage with each review activity multiple times. When they finished each attempt, they could view their grade and a summary of both correct and incorrect responses. This feedback included the correct answer for any wrongly answered question.

Both groups of students could access these review activities, which were optional and did not affect the students' final course grades.

C. Participants

The study was conducted within two practical groups of the Operating Systems course in the Computer Engineering Degree program. This course is part of the second academic year and was instructed during the second semester, spanning from February to May 2023. The experimental group comprised 20 students who had access to the visualization tool. Conversely, the control group was composed of 18 students who did not have access to the visualization system.

The gender distribution in the experimental group was $20\,\%$ female students, $80\,\%$ male students, and in the control group

6 % female students, and 94 % male students. These figures, while unbalanced by gender, align with the gender distribution of students in Computer Science degrees in the country where the study was carried out (omitted for blind review), with women representing approximately 16 % of students [reference omitted for blind review].

The learners did not possess any prior knowledge of the concepts taught in this course, as there were no other subjects in their curriculum that covered these or similar topics.

D. Procedure

As previously mentioned, this preliminary study was conducted during the practical classes of the Operating Systems course. All students had access to course materials on Moodle, such as class presentation slides, instructions for practicals, and the course calendar.

The course spanned 12 weeks, with students attending one two-hour class each week in the laboratory, with mandatory attendance. At the outset of the course, we introduced the visualization tool to the experimental group and explained its functionality.

Throughout the course, we covered various topics. Typically, each class was dedicated to explaining one of them, followed by student engagement with the topic. During these classes, we monitored student attendance and, upon conclusion, incorporated topic review activities into the Moodle course. Students' learning progress in the visualization tool was updated weekly based on the information explained in Section III-B. In weeks 5, 8, and 11 the students submitted their practical assignments and took a short exam on the topics covered in the preceding weeks. The scores for these activities were taken into consideration in the visualization tool in the update of the following week.

E. Data Collected

Concerning the data collected to analyze the impact of the visualization tool, the information is sourced from three different channels: attempts from review activities, interactions within the Moodle course, and students' final practical grades. Below, we explain the procedure and frequency to obtain these data.

1) Attempts from review activities: Once a week, we downloaded the attempts of the review activities in both groups of students. For each attempt, we collected the following data: the achieved score, whether the attempt was completed or not, the answers provided for each question, and the time taken for completion.

2) Moodle interaction data: Moodle incorporates tools for extracting all user interactions within the course. It is possible to get complete reports regarding system access, utilization of various materials, and more. Moodle allows to consult these records and provides the option to download them as CSV files for further analysis. We used this tool to extract information on how students engaged with the review activities, the visualization tool, and their final scores. Specifically, we extracted data about the access to the visualization tool, as well as about the scores achieved in practical assignments and exams. This information was extracted at the end of each course week.

3) Final scores: Finally, we gathered the final scores obtained for the practical part of the course for both groups of students at the end of the academic year.

F. Data Analysis

The current study followed a randomized controlled trial approach, by using both a treatment (experimental) and a control group. Students were randomly assigned to each group based on the university administration criteria, without any intervention from the researchers. The method allowed the gathering of data from both groups for comparison purposes, in addition to the specific experimental data from the treatment group, with access to the progress visualization tool.

The analysis of the data gathered followed a quantitative approach, as no qualitative data was captured. For both groups, we aggregated the number of attempts made on optional review activities, as well as their results in those attempts, and their final scores in all course practicals and exams. For the experimental group, we additionally aggregated their number of access to the progress visualization in each week of the course.

Data was combined from different sources (Moodle logs, teachers' records, etc.) by the lead researcher. The quantitative analyses were carried out by the lead researcher, and revised by at least one other author with extensive expertise in data analysis and descriptive statistics. Data aggregation and basic analyses were conducted with spreadsheet and analytical software.

In the following, we will explain the results obtained by analyzing the extracted data.

IV. Results and Discussion

A. Accesses to the Visualization Tool

The goal of the first analysis in our study was to understand how students from the experimental group had accessed the visualization tool. For this purpose, we examined the number of access per student and week.

Figure 3 shows the number of times that students displayed their learning progress. More than 20 accesses to the visualization tool were made in most weeks. It should be noted that, although week 9 obtained the smaller number of accesses, it was because it corresponds to the Spring Break at the university, a non-teaching period. In addition, weeks 1, 5 and 11 present a higher access than others. This can be attributed to two different reasons. On the one hand, accesses in week 1 seem to reflect that students are trying to get familiar with the visualization tool. On the other hand, weeks 5 and 11 correspond to weeks before deadlines.

Figure 4 displays a histogram of the number of accesses per student during the whole course, showing different behaviors. Eight students accessed at least 20 times in total, whereas seven accessed between 10 and 19 times. As we indicated in Section III-D, we updated the visualization tool once time per week, which means that 75 % of the students accessed it more frequently than it was updated, suggesting that they used the tool as feedback to analyze their status within the subject.

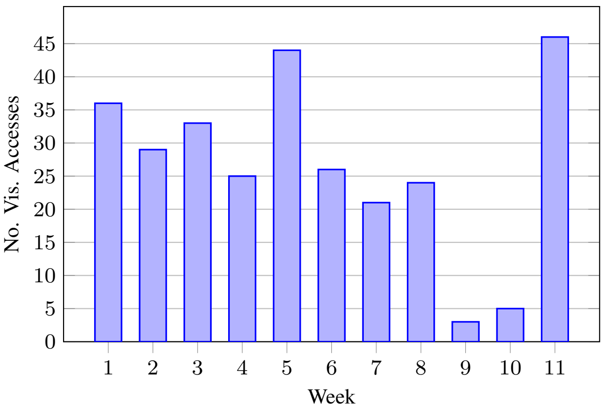

Fig. 3. Total number of accesses to the visualization tool per week of students in the experimental group.

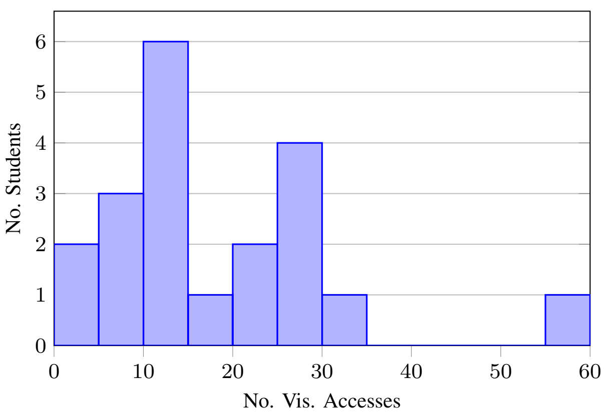

Fig. 4. Histogram of the total number of accesses to the visualization tool for students in the experimental group.

Finally, we represent the number of unique students that displayed their progress per week in Fig. 5. It can be seen that, in most weeks, more than 50 % of the students (minimum 11 out of 20) displayed their progress at least once, excluding holiday weeks.

Based on these results, we can draw a positive conclusion regarding **RQ1**: *Do students in the experimental group access the visualization tool consistently throughout the course?*. Students accessed the visualization evenly throughout the semester, except for the Spring Break. We did observe two trends: an initial surge in interest during the first week, following its presentation in class, possibly due to its novelty, as expected [35], and a subsequent increase in access during the final week of the course. This could be attributed to students seeking "prior insight" into their final course scores, despite the explicit disclaimer on the Moodle webpage that the progress displayed in the visualization tool does not necessarily correlate with their actual final marks. While not all students accessed the visualization tool an equal number of times, the average of once per week is reasonable, given the visualization's weekly updates.

Moreover, around half the students consulted it at least once every week during the course, aligning with the desired access ratio corresponding to the weekly updates. These findings

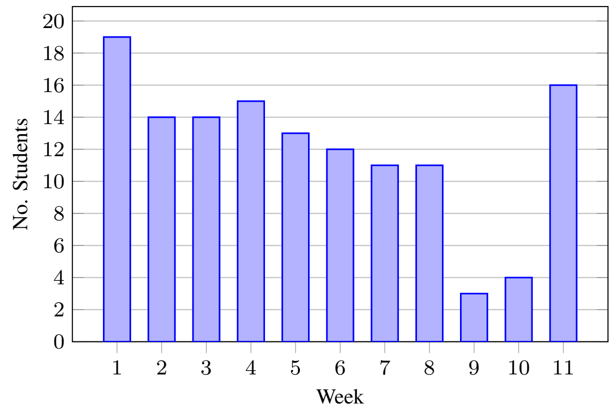

Fig. 5. Number of unique students in the experimental group that accessed the visualization tool per week.

demonstrate sustained student interest in monitoring their progress and continuously improving their results. Based on these results, the proposed visualization could contribute to students' self-regulated learning, by encouraging their reflection about their learning progress. This could be translated into different learning contexts, such as flipped classrooms, where reflection is one of the key design principles for self-regulated learning support [36].

In addition to the number of accesses to the visualization, we examined students' behavior after viewing their progress. As shown in Table I, all 20 students accessed the visualization at least once (2nd column), whereas 19 out of them completed at least one optional review activity (3rd column). For these 19 students, we analyzed the timestamps of their accesses to the progress visualization and the start times of their attempts at optional review activities. Specifically, we aimed to identify any patterns of accessing the visualization and subsequently engaging in optional review activities. We established a threshold of attempting review activities within the next two hours of accessing the visualization, as that was the time span of the weekly classroom lesson in the university laboratories. This review-after-visualization pattern was observed at least once during the course for 15 students (4th column). In particular, out of the total of 34 times this pattern occurred, 19 times the students completed a single review activity after accessing their progress visualization. The remaining 15 times students completed an average of 8 attempts in review activities.

These findings on behavioral patterns are inconclusive in addressing **RQ2**: *Do students in the experimental group engage in optional review activities after accessing the visualization tool?*. While we identified an interesting pattern in 15 students, which is a positive outcome, it occurred only a limited number of times. On some of those occasions, students completed several attempts at review activities after accessing the visualization, suggesting that they either wanted to see different review activities or improve their scores. This positive influence of the visualization on students' motivation to complete, in this case, optional review activities aligns with previous research indicating an increased motivation due to LA dashboards [33]. In our case, the data demonstrates that students completed numerous optional review activities and

TABLE I
NUMBER OF ACCESSES TO THE VISUALIZATION TOOL AND THE REVIEW ACTIVITIES, AND NUMBER OF TIMES THE REVIEW-AFTER-VISUALIZATION PATTERN WAS DETECTED FOR EACH STUDENT IN THE EXPERIMENTAL GROUP.

Student	No. Vis. Accesses	No. Rev. Activities	RaV Patterns
S01	5	0	–
S02	5	24	1
S03	56	40	4
S04	23	17	1
S05	10	80	2
S06	5	16	0
S07	20	34	1
S08	10	12	0
S09	26	25	5
S10	28	81	4
S11	27	41	3
S12	2	26	1
S13	13	72	1
S14	11	19	0
S15	11	19	2
S16	30	16	2
S17	18	62	2
S18	4	20	0
S19	25	35	1
S20	11	48	4

frequently accessed the visualization tool. However, these two aspects do not appear to be as closely related as anticipated. Conversely, it seems that optional review activities were compelling enough in themselves for students to complete them (without any information from the progress visualization) to review and enhance their understanding of the topics. This will be further investigated compared to the control group in **RQ3**.

Participation in optional review activities appears to be more concentrated near course deadlines, as students aim to prepare better for practical assessments, aligning with the approach of accomplishing tasks under the pressure of impending deadlines [37]. Similarly, visualization access was adequate, but it did not always correspond to subsequent reviews of topics in optional activities. However, this might be attributed to the fact that the learning progress visualization was not automatically updated immediately after an attempt at a review activity, but at the end of each course week.

Next, we will examine whether these accesses have motivated students to participate more in review activities, compared to those students who did not receive information about their progress.

B. Comparison of Review Activities Completed

In this section, we present the results comparing the distribution of attempts of review activities in both groups (experimental and control).

The first result pertains to the number of attempts made by each group. Table II presents the total number of attempts per topic. We observe an increase in the number of activities completed by the experimental group across all topics. The smallest increment was in topic T1 (30.2 %), while the most significant increases were in topics T4 and T5, where there were nearly twice as many attempts as in the control group. This result highlights that showcasing students' progress can bolster their engagement in the course.

TABLE II
COMPARISON OF THE NUMBER OF ATTEMPTS IN REVIEW ACTIVITIES BETWEEN THE TWO GROUPS IN EACH COURSE TOPIC.

Topic	Experimental	Control	Increase (%)
T1	82	63	30.2
T2	98	58	69.0
T3	88	58	51.7
T4	114	58	96.5
T5	101	53	90.6
T6	99	70	41.3
T7	89	62	43.5

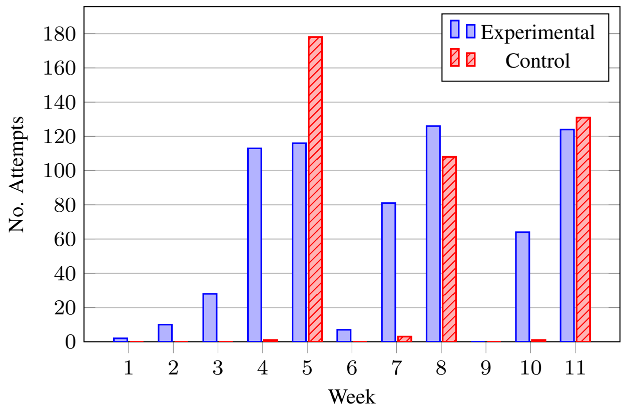

Fig. 6. Number of attempts in review activities per week in both groups (experimental and control).

This data yields a positive result concerning **RQ3**: *Do students in the experimental group complete more optional review activities compared to students in the control group?*, and aligns with previous research that pointed out how awareness information, visual feedback, and social comparison can foster students' participation in learning environments [38]. The impact of the visualization on these results needs to be contextualized with the findings of **RQ2**, as the pattern of attempting a review activity after accessing the visualization, while not highly common, was indeed observed at least once for a total of 15 students. Thus, it contributes to these higher numbers in the experimental group, indicating a situation of increased motivation driven by heightened awareness [33].

Another finding can be derived from Fig. 6 comparing the number of attempts carried out weekly in both groups. The control group had the most significant number of attempts in optional review activities during the weeks of practical deadlines (weeks 5, 8, and 11). The participation of the control group during the rest of the weeks was very low or non-existent. However, students from the experimental group participated in the rest of the weeks (except week 9 of Spring Break). While participation is highest in the weeks of practice deadlines in both groups, only in the experimental group we also observe significant participation in the weeks before deadlines.

The distribution of attempts in optional review activities reveals mixed results for **RQ4**: *Do students in the experimental group engage in optional review activities more evenly throughout the semester compared to students in the control*

TABLE III
COMPARISON OF AVERAGE SCORE OVER ALL THE ATTEMPTS IN REVIEW ACTIVITIES BETWEEN THE TWO GROUPS IN EACH COURSE TOPIC.

Topic	Experimental	Control	Difference
T1	8.37	8.10	+0.27
T2	7.65	6.95	+0.70
T3	7.69	7.82	−0.13
T4	7.57	7.87	−0.30
T5	8.22	8.05	+0.17
T6	8.89	8.76	+0.13
T7	8.73	9.09	−0.36

group?. Both groups exhibit their highest number of attempts in the weeks preceding course deadlines, underscoring the greater impact of these deadlines compared to the visualization, consistent with the notion that deadlines and effective time management can significantly influence learning [37]. However, we observed that students in the control group barely made any attempts at optional review activities apart from those weeks. In contrast, there are additional attempts in the experimental group which could be partially attributable to the progress visualization.

C. Comparison of Activities and Final Scores

Finally, we analyzed whether there was a difference in the learning results of both groups of students. To do this, we examined the marks obtained in the review activity attempts and the final course grades.

Table III displays the average scores achieved by students in the experimental and control groups across the different topics. For each row, the last column presents the calculated difference between the two values (experimental minus control). In particular, students in the experimental group achieved higher average scores in four topics, while students in the control group performed better in the remaining three topics. The greatest difference is observed in T2, while the other course topics have closer average scores.

These results do not provide a definitive answer to **RQ5**: *Do students in the experimental group attain higher average scores in the optional review activities compared to students in the control group?*. We can also link this to **RQ4**, noting that students in the experimental group may make more attempts to improve their scores, thereby elevating their overall average score per topic. One possible explanation for this heightened motivation could be the visualization itself, as the achieved scores impact the progress displayed on the visualization in subsequent updates (increasing the progress estimation if the results were indeed higher).

The last comparison involved the final scores for the practical part of the course in both groups. The average final score for the experimental group was 6.25, whereas the average for the control group was 7.00. We conducted a Mann–Whitney U test which yielded a p-value of 0.57, therefore implying that there is no significant difference between both groups. However, this still constitutes a negative result concerning **RQ6**: *Do students in the experimental group achieve higher final scores in the course than students in the control group?*. Consequently, we scrutinized the results in the other six groups of the course (excluding both the experimental and control groups), all of which are part of the same degree program. We found that their average score was 6.14, with four of those six groups having an average final score lower than that of the experimental group. Therefore, we may conclude that, although the visualization does not appear to have a positive impact on the final course results for students in the experimental group, their performance is comparable to that of other groups in the course.

V. CONCLUSIONS

The present study aimed at exploring the use of a visualization tool to increase student's awareness of their progress in the different topics of a university course. The study described the design of the visualization, including the learning activities that contributed to it, and measured the effect of such visualization on students' motivation to improve their results by participating in optional review activities available for each topic. To evaluate the impact of the proposed visualization, we compared an experimental group of students, who accessed a visualization about their progress, and a control group, without access, during a full semester.

Results showed that the visualization tool was widely used by most students throughout the course. We identified two significant points of access: during the first weeks, attributed to its novelty, and in the final week, for result checking. These findings demonstrate students' interest in visualizing their progress. However, we found no solid evidence of students engaging in review activities immediately after visualizing their progress. This might be attributed to the lack of automatic updates in the visualization progress tool, resulting in a delayed impact from optional review activities on the visualized topics' progress.

Other noteworthy results pertain to the review activities undertaken by the experimental and control groups. The visualization had a positive impact on students' motivation to attempt optional review activities. While both groups used these activities over the semester, the experimental group used them significantly more. Furthermore, distinct patterns were observed in the timing of activity completion: the control group concentrated their activities around deadlines, whereas the experimental group spread theirs out between the deadline week and the preceding weeks.

The final analysis of the results focused on the course scores. However, the study did not find any impact of the visualization tool either on the activities or on the final marks.

The main conclusion drawn from this study is that the use of the visualization tool increases student participation. Not only did the visualization tool foster a higher participation in review activities, but it also spread it more evenly over time.

A. Limitations

The number of participants in both groups (approximately 20 students) is the first limitation that affects the generalization of our results. The gender distribution of the participants could also bias our results, although it is representative of the student population in Computer Science degrees in the country where the study was carried out. Some issues were also encountered during the development of the visualization tool, such as the manual updating of the progress weekly. These limitations will be addressed in future work, which is elaborated upon below.

B. Future work

As further lines of work, we plan to increase the number of participants by extending the use of the visualization tool to gather data from more participants in future years. The compilation of a larger dataset is expected to validate the positive results suggested by this study. Additionally, conducting a questionnaire among students participating in the experimental group could provide further insight into their use of the visualization and their perception of it. A broader range of review activities could also benefit participation as well as the analysis of students' progress to recommend them individually (e.g., suggesting review activities of topics with lower progress achieved). Furthermore, we are currently improving and automating the visualization tool, to contribute to its use by a larger number of teachers and courses within the university. Simultaneously, we are exploring the possibility of creating and publishing a Moodle plugin based on the visualization tool to be officially integrated by the university. The new version of the visualization tool will be examined for integration into other university courses where a similar division into topics is feasible, along with optional review activities to complement the student's learning process.

Considering the positive results of the present study and the upcoming improvements, we believe that this case study could be adapted for other courses and universities, being a learning analytics tool to increase students' awareness about their progress and help them increase their active participation in their learning process.

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